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Supporting 3PL Decisions in the Automotive Industry by Generating Diverse Solutions to a Large-Scale Location-Routing Problem

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For the distribution of spare parts to car dealers, many automotive companies use a transport network of intermediate hubs or transport platforms, operated by a set of third-party logistics (3PL) partners. The optimization of this network, particularly the selection of 3PL providers and corresponding transport platforms, is a complex decision that needs to be supported by appropriate software tools. In this paper, we develop such a tool, implement it, and show its results on a real-life case study provided by Toyota. The tool is currently in active use at Toyota to study and improve the distribution of spare parts in Germany.

Using a tabu search metaheuristic, the developed tool essentially solves a large location-routing problem, but has several innovative features to increase its usefulness. First, the tool generates a set of high-quality but structurally different solutions, rather than a single one. This increases Toyota’s negotiating power, increases its ability to analyze its current transport network against possible alternatives, and allows it to quickly switch between different transport networks if unexpected events occur. Second, a commercial vehicle-routing solver is integrated into the tool, to allow for a far more realistic modeling of the vehicle-routing decision.

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1. Introduction

In this paper, we describe the solution of a real-life location-routing problem faced by a large automotive company, Toyota. For the distribution of spare parts to car dealers in Europe, Toyota operates two hubs, one in Germany and one in the Czech Republic. During the day, dealers may call to place orders for spare parts that are to be delivered before the next morning. Such a call triggers a flow of handling actions in one of the hubs. The parts are first picked and readied for transportation. Then, they are combined into full truckloads (FTL) and transported to an intermediate transport platform. Essentially, a transport platform is a warehouse or depot with some (limited) facilities for handling and cross docking. All transport platforms are owned and operated by a third-party logistics (3PL) provider. At the transport platforms no inventory is held. Items received from the hub are sorted and loaded onto (usually smaller) trucks for delivery to the car dealers the same night. These smaller trucks then deliver the spare parts to the different car dealers in milk runs. Toyota promises next-day delivery for all orders placed. Decisions on the importance of orders, and whether nonurgent orders of several days should be grouped and ordered in a single batch are left to the individual dealers. Most dealers, however, place an order each day. The order and delivery process of spare parts to car dealers is shown in Figure 1.

One of the most important problems faced by Toyota is the selection of 3PL providers and their corresponding transport platforms. Because of the importance of this decision, the company tenders a large number of potential 3PL partners, including ones with which it has already worked and others with which it has not. The 3PL providers will bid on a—usually geographically restricted—part of the distribution of spare parts. One 3PL provider may, for example, bid on the distribution of spare parts in one or two German provinces. When the tendering process is over, Toyota has a list of potential 3PL partners, with overlapping potential for delivery of spare parts. Determining Toyota’s transport network—i.e., which providers to select and which not—is a difficult process that involves a constant iteration of negotiation and evaluation.
In this paper, we describe the development of a decision-support tool to support the process of determining a transport network. Several factors make evaluating potential transport networks and determining an adequate transport network especially difficult in this case:

- Because each of the potential 3PL partners may bid for a different part of the total distribution effort, based on its vehicle fleet and the location and capacity of its transport platforms, it is very difficult to determine the “cheapest” service provider. Hourly costs or costs per kilometer are generally heavily influenced by geographical differences between different regions (e.g., delivering in a densely populated industrial region is much more efficient than delivering the same amount in a mountainous region). The company therefore needs a way to determine whether the price structure proposed by the potential partner is indeed reasonable. Moreover, determining the “cheapest” service provider for a region is not a decision that Toyota can make independently from other regions because those regions are overlapping. It is the combination of several service providers that makes a transport network effective and/or efficient.

- There is considerable uncertainty with respect to some decision factors, especially for potential 3PL partners with which Toyota has no experience. This is true for factors that are easy to quantify, such as costs, but even more so for factors that are typically hard to quantify. In the past, the company has had bad experiences with the service level obtained by some logistics providers, which did not correspond to the quoted or required service level. Moreover, the 3PL provider’s handling quality is especially important and determines to a large extent the number of spare parts that are returned because of defects. It is very difficult to quantify the handling quality of a 3PL provider with which the automotive company has had no previous experience.

- In the fast-moving 3PL market, few things stay the same. The quality of a 3PL partner with which the company has a steady relationship can therefore decrease at any time. At this point, the company may decide to stop working with a certain provider, in which case it needs to determine an alternative network of transport platforms.

- The complexity of the real-life logistics network underlying the 3PL partner selection process makes accurately calculating the total network cost very difficult without accounting for significant operational detail. Ignoring such issues as time windows, vehicle types, capacities, and size limitations, as well as road network issues, would result in poorer decisions as a result of poorly calculated costs.

In this paper, we describe the development and implementation of a decision-support tool for the design of a transport network—i.e., the selection of 3PL providers—that is especially designed to overcome the difficulties mentioned above. Starting from Toyota’s own decision-making process, which values cost precision over analysis speed, we have created a tool that has at least two innovative features.

First, it generates a set of structurally distinct solutions, all of which have a high quality, rather than a single one. To this end, it uses tabu search to find good solutions and the Hamming distance metric to ensure that solutions are sufficiently different before storing them in an archive. Generating structurally different solutions offers insight into the different feasible transport networks, and allows the company to switch more easily and knowledgeably between transport networks in case unexpected events occur. Moreover, it increases Toyota’s power to negotiate on a tactical level (i.e., the selection of 3PL providers) because it offers a profound insight into the cost structure of the different alternative transport networks, and therefore
allows Toyota to determine its margins for negotiation with its (potential) 3PL partners.

Second, it solves the routing problem as a part of the transport platform selection problem by incorporating a commercial vehicle-routing solver. As mentioned, Toyota delivers a large majority of its spare parts to intermediate transport platforms, and outsources the final delivery of spare parts to the dealers to a set of 3PL providers. In principle, Toyota therefore does not have to determine the customer scheduling and routing. However, doing so enables the company to better evaluate the proposals by the 3PL providers and gain a more thorough understanding of the problem it faces. Although there is considerable theoretical support (see §2) that incorporating operational details can result in better strategic or tactical decision processes, this insight is not often applied in theory or in practice. In this specific case where transport is partially outsourced, another advantage is that the detailed routing plans resulting from our tool result in a better negotiating position with respect to (potential) 3PL partners. The tool provides Toyota with a very accurate estimate of the distribution cost of their 3PL partners, which results in a deeper insight into how the 3PL partners make their decisions. Large deviations between these cost estimations and the prices quoted by the 3PL partners are subject to investigation and negotiation. Moreover, the solutions proposed by our tool are generally easier to implement than those proposed by higher-level decision-support tools because many fewer practical details will have been overlooked during the tactical decision-making phase.

The problem solved by our tool therefore consists of two subproblems that are solved simultaneously: (1) selecting 3PL providers and associated transport platforms to use, and (2) determining milk runs to visit the car dealers from the selected transport platforms. Such a problem is known in the literature as a location-routing problem.

2. Literature Review

Unsurprisingly, location-routing problems are very difficult because both subproblems (facility location and vehicle routing) are NP-hard. Recently, this problem has seen some renewed research interest. Previous surveys can be found in Balakrishnan et al. (1987) and Min et al. (1998). The most recent survey appeared in Nagy and Salhi (2007).

The lack of research interest in the past might be attributable to the difference in planning horizon between the two problems. Location decisions are typically perceived as being on the strategic, long-term level, whereas routing decisions are generally on the operational, short-term level. Because of the fact that vehicle routes are usually reoptimized each day, whereas the relocation of distribution facilities may not be done for many years, researchers have often proposed to solve the location and routing problems separately. Nevertheless, it has been pointed out that neglecting routing while locating depots leads to inferior results (Rand 1976, Salhi and Rand 1989). Solving the integrated location-routing problem can decrease costs even over a longer time period (Salhi and Nagy 1999). These arguments hold for the problem faced by Toyota. Moreover, the difference in planning horizon between location and routing decisions is much smaller in this problem because the choice of transport platforms is far less difficult to change than the physical location of distribution facilities owned by Toyota itself.

Algorithms for location-routing problems can be divided into two categories: (1) those that come with a guarantee of finding the optimal solution (exact methods), and (2) those that do not (heuristic methods). Although some exact algorithms have been developed for location-routing problems (Laporte and Nobert 1981, Laporte et al. 1988), these methods are limited to tackling small instances, except in some special cases, e.g., Labbé et al. (2004). For large-scale, real-life problems, (meta)heuristic approaches seem to provide more tractable alternatives. As a result, heuristic methods are far more common than exact ones. For an overview, we refer to Nagy and Salhi (2007).

The survey of Nagy and Salhi (2007) lists a large body of location-routing papers and discusses several factors such as the planning period, objective function, route structure, etc. The authors classify heuristics for these problems into different categories based on the way in which the location problem and the routing problem are integrated and how information is passed on between the two subproblems.

Sequential methods work in two phases, solving the location problem in the first phase (using either the distance of the customers to the depot or some form of route-length estimation) and the routing problem in the second. No information is passed back from the routing problem to the location problem, and hence these methods can be viewed as two separate methods, instead of one. Although these methods can provide good results in some cases, they are generally not recommended because their results may be very poor (Balakrishnan et al. 1987).

Cluster-based methods—e.g., Barreto et al. (2007)—are similar to sequential methods in that no feedback from the routing to the location problem takes place, but are different in that they first attempt to divide the customers into clusters (one per depot and one per route). This approach provides a more sensible way of integrating routing and location decisions.

In iterative methods, such as the method by Hansen et al. (1994), the routing problem and the location problem are solved iteratively, passing information about the solution of each subproblem to the solution method for the other subproblem. Generally, these methods end when neither of the phases yields an improvement.

Although iterative methods present an improvement over cluster-based methods, they still have some of their drawbacks, resulting from the fact that these methods treat both decisions as if they were on the same level. In contrast, hierarchical or nested heuristics take into account the
difference in planning horizon and view the routing problem as a subordinate problem to the location problem. This viewpoint is motivated by the observation that routing costs are highly dependent on the location of facilities and that both subproblems can therefore not be considered separately. The heuristic developed in this paper, which is a variant of the one by Nagy and Salhi (1996), is an example of a hierarchical method.

As mentioned in the introduction, our method generates a limited set of solutions, all of which have a high quality (low cost), but which are mutually structurally different. This approach is advocated by Barreto et al. (2007), among others. It has long been recognized that mathematical programming models typically leave out a lot of details and use approximate data (Sharda et al. 1988, Hoch and Schkade 1996). The archive of structurally different solutions generated by our method is used for decision support: to supply the decision maker with a set of high-quality alternatives. A similar approach is taken in Glover et al. (2000). An archive of high-quality, structurally different solutions is used in some metaheuristic approaches to improve the quality of the solutions found (Sörensen and Sevaux 2006).

3. Solution Method

Our method for solving the location-routing problem is based partly on the nested heuristic method proposed by Nagy and Salhi (1996), but extends the method by incorporating long-term memory and embedding a commercial routing solver. Moreover, a mechanism to generate a small, diverse set of high-quality solutions is added. In the next few paragraphs, we give a general overview of our method, after which a more detailed explanation on some interesting features (memory structures, integration of a commercial routing solver, and archiving mechanism) follows.

3.1. Overview

A solution in our method corresponds to a status “selected” or “not selected” for each potential transport platform. Let \( n \) be the total number of potential transport platforms; then a solution can be represented as a binary string of size \( n \), where a one or a zero in position \( i \) means that platform \( i \) is respectively selected or not selected in this solution. Note that this solution representation does not encode the routing decisions, which are left for the commercial routing solver to take (see §3.3).

An initial solution is chosen arbitrarily by the user. Usually, the current situation is taken as a starting point. This is a good starting solution as a result of Toyota’s continuous improvement efforts.

At each iteration, our method starts from the current solution and checks which move decreases the objective function value the most. The neighbourhood of a solution is defined by the union of three different moves: selecting an unselected transport platform \((add)\), unselecting a selected platform \((drop)\), and a move that combines selecting an unselected transport platform and unselecting a selected one \((swap)\). The number of moves checked at each iteration is equal to the sum of the number of platforms \( n \) and the number of selected platforms \( m \) times the number of unselected ones \( n - m \), i.e., \( n + m(n - m) \). Determining the objective value \((cost)\) of the solution is done using a commercial routing solver. When no moves can be found that decrease the cost, the move is selected that results in the smallest possible cost increase.

When no new solutions have been added to the archive (see §3.4) for a fixed number of \( I_{\text{max}} \) iterations, our method reinitializes by starting from a new solution. This solution is generated randomly, by choosing each transport platform equally likely.

The algorithm ends when a maximum number of reinitialisations \( R_{\text{max}} \), determined by the decision maker, has been reached.

A schematic overview of our tabu search procedure is shown in Algorithm 1.

\begin{algorithm}
\caption{A tabu search procedure for location-routing:}
\begin{algorithmic}
\State Choose arbitrarily an initial solution \( s_0 \);
\While{number of reinitialisations \( \leq R_{\text{max}} \)}
\While{number of nonarchive updates \( \leq I_{\text{max}} \)}
\State determine best move \((add, drop, swap)\) that is not tabu or satisfies the aspiration criterion;
\State implement move and put reverse move in the tabu list;
\If{adding conditions for the archive hold}
\State add solution to archive;
\Else
\State number of nonarchive updates++;
\State update frequency memory;
\State unselect most selected platform and put opposite move in the tabu list;
\State select least selected platform and put opposite move in the tabu list;
\State number of reinitialisations++;
\EndIf
\EndWhile
\EndWhile
\EndWhile
\end{algorithmic}
\end{algorithm}

3.2. Tabu Search Memory Structures

To prevent the search from quickly getting stuck in a local optimum, we apply three different memory structures from the tabu search literature.

The tabu list, or recency memory, stores the \( t \) most recent moves. The parameter \( t \) is referred to as the tabu tenure, and determines how long a move remains on the tabu list. When a move appears on the tabu list, this move is forbidden for \( t \) iterations. In this way, looping is prevented, i.e., the behaviour in which the search converges to a very small region of the search space and keeps repeating the same small set of moves in the same order. The tabu tenure \( t \) is a parameter of the algorithm, the value of which is determined experimentally through a small pilot study.
**Frequency memory** is used to further diversify the search. The frequency memory stores the number of times each transport platform has been selected in the active solution. This long-term memory is used periodically, when no improving solutions have been found for a certain number of iterations. At this moment, the most frequently used transport platform is unselected, and the most infrequently used one is selected. This move is also put on the tabu list to prevent the method from immediately reverting to the previous solution. This type of memory is essentially used to prevent the method from immediately reverting to the previous solution. This type of memory is essentially used to force the search to look in different regions of the search space, and hence consider solutions that are structurally different. Given the problem with which we are faced—generating a diverse set of high-quality solutions—we find that using this type of memory is especially appropriate and even necessary.

Finally, **aspiration memory** is used to store the best solution encountered thus far. The so-called **aspiration criterion** temporarily overrides the tabu list in cases where it would prevent the method from finding a solution better than the best one found so far.

### 3.3. Integration of a Commercial Routing Solver

A novel feature of our approach is that it integrates a commercial routing solver, SHORTREC, developed by the company ORTEC (http://www.ortec.com). This solver is used to calculate the objective function value given a solution, i.e., a set of selected transport platforms. SHORTREC estimates the cost of a given transport network by solving a multilevel, multidepot vehicle-routing problem, in which each of the selected transport platforms is considered a depot. Most hierarchical location-routing approaches use an “academic” vehicle-routing formulation to determine the routing cost. These formulations are highly simplified versions of the “real” vehicle-routing problem at hand. Our approach, however, allows us to use a far more realistic model of the real-life problem, capturing many more aspects than would be tractable by hand-developing the vehicle-routing solver. One of the important advantages of this approach is that it allows for far better platform location decisions than would be possible with an academic routing model. The main reason for this is that the use of a commercial solver significantly increases the accuracy of the (difficult) cost calculations in the entire transport network compared to those produced by an (over)simplified model. The drawback of this approach is an increase in computation time.

Using a commercial routing solver as part of the transport platform selection tool allows Toyota to evaluate the proposals by the potential 3PL partners. In the past, this was done by requiring the 3PL providers to produce detailed routing plans, which were manually checked. Our tool allows Toyota to evaluate these plans more systematically, by comparing them to the routing plans determined by its own routing software. In other words, to evaluate the price structure proposed by a potential 3PL provider, the planning department of Toyota temporarily puts itself in its shoes and does all the required calculations using its own software. The main benefit of this approach is that it gives Toyota a large amount of negotiating power. If the prices of a logistics provider are too high because of, e.g., poor planning of routes, the company can demonstrate this empirically. It can also determine which 3PL providers tend to force prices to be unreasonably low, probably indicating a lack of realism in their planning effort, which in turn will lead to future problems if the quoted prices prove to be insufficient to cover the costs. Finally, this approach gives Toyota a birds-eye perspective on the entire transport network design problem because it becomes possible to determine the impact of a decision (e.g., the selection of a transport platform) on the other 3PL partners, as well as on the entire network.

SHORTREC is a highly versatile vehicle-routing solver that is deployed to aid in the planning and scheduling of transport at a multitude of small and large companies. As a package for real-life vehicle routing, SHORTREC is able to model a large number of characteristics specific to our problem.

In this specific case, the vehicle-routing problem that was solved by SHORTREC includes time windows at the dealers and earliest departure times at the hub. Fourteen different truck types are defined, and are linked to the different 3PL providers. Moreover, for each dealer a list of allowable vehicle types is defined (e.g., some dealers are located in places that are difficult to reach and hence cannot be serviced by large trucks). Constraints on the route (e.g., maximum driving time due to driving time legislation), as well as three different capacity constraints (weight, volume, and number), are defined. SHORTREC calculates all driving times and distances between dealers and transport platforms over a detailed road map before starting the optimization. This is done optimally through the use of the well-known Dijkstra algorithm. Per road type, a speed is defined that an average vehicle will attain. Per vehicle type, a multiplication factor is defined that determines its relative speed compared to that of an average vehicle; for example, large trucks of a certain type are only able to drive at 90% of the average speed. A fixed handling time at the transport platform, as well as a fixed unloading time at each dealer, is also included in the calculations.

The objective function that is optimized by SHORTREC is total cost. This cost is based on estimates of the real cost incurred when using a vehicle and is a combination of a fixed cost, a variable cost per kilometre, and a variable cost per hour.

Besides determining the routes from the hubs to the dealers, SHORTREC also calculates the cost of full truckloads to ship from the hubs to the transport platform. Costs of these full trucks are also taken into account in the objective function. The ability of SHORTREC to plot the proposed routes on a map and the ability to manually adjust the routing and see the effects of these operations also contribute to the usefulness of this approach.
A detailed description of the algorithms used in SHORTREC is beyond the scope of this paper. Summarizing, we can state that it uses a combination of constructive heuristics to find good initial solutions quickly and some form of variable neighbourhood search to improve upon these solutions. In this variable neighbourhood search, several neighbourhood structures are used, the order and frequency of which can be determined by the user. In a way, these neighbourhoods can be used as “building blocks,” to create a heuristic solution method that is adapted to the specificities of the routing problem at hand. In this way, the solver can be adapted by the user, so that a balance is reached between computing time and solution quality. Moreover, the user can exercise a large degree of control over the length of the search.

Of course, this approach has some disadvantages. First, the fact that SHORTREC takes all the mentioned complex constraints into account results in a solution method that is slower than approaches that are less powerful in this respect. Moreover, the modular and flexible code of SHORTREC results in a slower optimization process than that of other solvers that have been written to solve a single specific vehicle-routing problem. These concerns are partially offset by the fact that the SHORTREC code has been created through many man-years of continuous improvement, but given the fact that the objective function has to be calculated quite a large number of times (each time a potential transport network is evaluated), our approach requires several hours of computation time to solve the problem. However, given the strategic importance of the decision, this is not considered an insurmountable problem. Together with Toyota, it was decided that the precision of the cost calculations, based on a solution that takes a large number of practical characteristics of the problem into account, is more important than calculation speed. Several steps were nevertheless undertaken to reduce the computation time.

To reduce the time required to resolve the vehicle-routing problem each time a transport network is evaluated, we adopt the notion of influence region (Nagy and Salhi 2007). The motivation for using this notion is that it is rather unlikely that the selecting or unselecting of a transport platform will have a large influence on the delivery routes from transport platforms located far away. Therefore, only customers located within a radius of $M$ minutes ($M$ is a parameter, to be set by the user) from a transport platform that is selected or unselected are reallocated and inserted into existing or new routes of a selected transport platform. This considerably reduces the size of the routing problem that needs to be solved. A partial reoptimization of the solution is a feature explicitly present in SHORTREC and is very useful for manual tuning of the plan.

Another time reduction scheme is to use two different configurations of SHORTREC. In its full configuration, SHORTREC is used to evaluate whether the quality of a solution is high enough for it to be added to the archive. This full configuration, however, is rather time-consuming. Therefore, to guide the search—i.e., to determine the best possible move—SHORTREC is used in a reduced configuration. In its reduced configuration, SHORTREC solves the routing problem for a given transport network by only using a fast constructive heuristic, followed by a heuristic that attempts to reallocate routes to another transport platform. In its full configuration, SHORTREC uses a wide variety of different heuristics to determine the lowest possible routing plans for a given transport network. The routing problems solved in both configurations are the same, only the depth of the search varies.

### 3.4. Archiving Mechanism

Instead of presenting the decision maker with one single solution, our tool presents him/her with an archive of several solutions that have a different structure in terms of selected transport platforms. This has several advantages. First, when changes occur in the network (e.g., a certain 3PL provider stops meeting the required standards), a different network can be chosen at short notice, without having to reoptimize. Second, determining alternative transport networks gives a much larger negotiating power to the decision maker. Because several options are known in advance, it becomes much easier for Toyota to determine the relative value of a certain 3PL provider, knowledge that it can use to its advantage in the negotiating process. Third, the decision maker may choose from the list of good but diverse solutions the one that is the most practical to implement, and take into account factors that are otherwise difficult to quantify.

The archiving mechanism built into our tool maintains a list of high-quality solutions that are structurally diverse. The diversity of solutions is measured as a distance in the solution space. We therefore require a measure of the distance (or similarity) between two solutions. To calculate this distance, we only consider the location part (the binary representation of selected and unselected transport platforms) of the solution, and hence disregard the routing part. This is motivated by the fact that the aim at this stage in the decision-making process is to select transport platforms and not determine detailed routing plans.

To calculate the distance $d(s, t)$ between two solutions, our method uses the Hamming distance. Given two solutions, represented as binary strings of equal length, the Hamming distance is equal to the number of transport platforms with a different status (selected/unselected) in both solutions. In symbols,

$$d(s, t) = \sum_i |s[i] - t[i]|,$$

where $s[i]$ is the binary value of the status (0 or 1) of transport platform $i$ in solution $s$. The distance of a solution to the archive is calculated as the minimum distance to any solution in the archive $A$, i.e.,

$$d_A(s) = \min_{t \in A} d(s, t).$$

The quality of a solution $s$ is determined by two measures: its cost $f(s)$ and its service level $l(s)$. A solution...
is not added to the archive if its cost is more than a certain percentage $\delta$ above the cost of the best solution in the current archive.

A minimum service level $L$ is imposed for all of the solutions in the archive. The service level is calculated as the planned number of dealers, divided by the total number of dealers. The service level is generally set to a high percentage, such as 99%, but is introduced because scheduling all dealer orders is generally impossible (due to the lack of transportation capacity) or prohibitively expensive.

Summarizing, after each move in the tabu search procedure, the quality of the current solution $s$ is evaluated using SHORTREC in its full configuration. In this evaluation phase, both the cost $f(s)$ and the service level $l(s)$ are determined. Also, the distance of the solution to the archive $d_A(s)$ is calculated. The current solution $s$ is added to the archive if the following three conditions hold:

1. The cost of the solution is less than $\delta$ per cent above the cost of the best solution found so far, i.e., $f(s) < (1 + \delta) f(s_{\text{best}})$.
2. The distance to the archive of $s$ is larger than a threshold $D$, i.e., $d_A(s) \geq D$.
3. The service level (number of planned dealers divided by the total number of dealers) is at least equal to a certain service-level threshold $L$, i.e., $l(s) \geq L$.

The maximal cost deviation from the best-found solution $\delta$, the minimum distance to the population $D$, and the minimum service level $L$ are three parameters that can be set by the user.

The archive $A$ has a fixed size. When the archive is full, the new solution replaces the “closest” solution from the archive, i.e., the solution in the archive to which its Hamming distance is minimal. When the closest solution is $s_{\text{best}}$, i.e., the best solution in the archive so far, it replaces the second-closest solution. This guarantees that the best solution found so far always remains in the archive. Using the Hamming distance guarantees that the solutions in the archive are structurally different from each other and are therefore real alternatives for the “best” solution, rather than variations of it. As a “fortunate by-product” of its aim, which is to find solutions that are diverse, it does also increase the quality of the search by diversifying.

4. Initial Results

The method described in the previous section was implemented and tested in cooperation with the planning department of Toyota’s European parts distribution centre in Diest, Belgium in a pilot test phase that took approximately one and a half years (August 2005 to January 2007) to complete. In this section, we describe the initial results of the tool. The day-to-day usage of the tool at Toyota is summarized in §5.

The tool is developed to determine the transport network that is used to deliver spare parts to dealers in Germany. In this problem, around 800 dealers have to be serviced each working day. If a dealer orders its spare parts before the cutoff time of 16h00, the company promises delivery before 9h00 the next morning. In Germany, at least 65% of the dealers place an order every day. Although there are some daily variations in demand (ordered volumes are highest on Mondays and Tuesdays and lowest on Fridays), most dealers have a fixed weekly ordering strategy, so that weekly variations are extremely small. Another reason for the small variations is the inventory strategy used by Toyota. As mentioned, no inventory is kept at the transport platforms. Apart from conforming to Toyota’s well-known inventory reduction strategies, this essentially reduces the potential impact of the bullwhip effect by reducing the number of intermediate distribution stages. For these reasons, the tool is run on the data of a “representative” week (i.e. a week without extraordinary events). The average volume ordered per dealer per day is 0.7 m$^3$, but individual orders vary greatly, depending on the dealer size. Some dealers order below 0.1 m$^3$ per day, whereas others have orders of around 7 m$^3$ per day.

Before the implementation of our tool, Toyota operated 14 transport platforms. For this implementation, 99 additional candidate transport platforms spread over Germany were defined. These potential transport platforms and corresponding 3PL partners could be classified into three categories, depending on the amount of information available:

- existing platforms of current 3PL partners,
- existing platforms of potential 3PL partners, and
- nonexistent transport platforms.

For 3PL partners in the first category, very accurate pricing information was available. In addition, Toyota had excellent insight into the fleet of the 3PL partners stationed at the transport platform (number of vehicles for each vehicle type, capacity…). The information on the transport platforms in the second category was obviously more uncertain, due to the lack of experience with the 3PL partners in this category. Only information gathered during the tendering process could be used. The last category was added to define interesting transport platform locations/areas for which no information was received. Being an important customer, Toyota usually has the power to persuade a 3PL partner to invest in a new transport platform, should this prove necessary. For these transport platforms, average pricing and fleet information was used.

A 95% service level was imposed, but the algorithm never examined a solution with a service level below 99.8%. In fact, in all solutions encountered, SHORTREC was able to plan all customer orders except for one. This customer order was issued by a dealer located in a very remote area, that could only be reached by ferry. It proved impossible to reach this dealer within the preset time window from any potential transport platform.

The tabu search algorithm was run for approximately 20 hours, evaluating over 220 configurations during this time. As mentioned, computing time is considerable, but is considered a minor issue given the strategic importance of the decision.
Table 1. Summary results.

<table>
<thead>
<tr>
<th>#</th>
<th>Cost (% of current)</th>
<th>N</th>
<th>Avg. Hamming distance</th>
</tr>
</thead>
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The archive of diverse solutions was set to contain 10 solutions, one of which the current solution. At the end of the algorithm run, the diverse solution archive contained the solutions depicted in Table 1. This table shows the solution number (#, solution 10 is the current situation), the cost per day of this solution in percentage of the cost of the current solution, the number of open transport platforms N, and the average Hamming difference from the other solutions in the archive. Cost threshold δ and minimal distance D were, respectively, set to 10% and 3. A graphical representation of the best solution is shown in Figure 2.

The best solution found by the algorithm is over 8% cheaper than the current solution, while keeping the same service level (99.8%). It is interesting to note that solutions using more transport platforms are not necessarily more expensive if the combination of transport platforms in the network is well chosen, i.e., a larger decrease in secondary distribution costs offsets an increase in primary transport costs. It should be noted that the cost reported by the tool is only an estimate of the actual cost and that the cost savings should not be taken at face value, but rather analyzed in detail. This is explained in §5.

In the best solution, a transport platform from the third category was included (i.e., a potential transport platform that does not yet exist). This same transport platform also

Figure 2. Best solution.

Note. ORTEC product screen shot reprinted with permission from ORTEC.
 occurred in the second- and third-best solution. However, if the nonexisting transport platform cannot be set up for some reason, there is still a way around this as the archive contains a number of very good solutions in which this platform is not selected (such as solution 4). However, these results show that setting up this transport platform is very important if Toyota wants to reduce its costs further. This example shows that the extra information obtained from analysing a number of excellent solutions facilitates the decision process of setting up new transport platforms and clearly demonstrates the usefulness of producing several structurally different solutions instead of a single one.

5. Usage and Benefits of the Tool

From January 2007 on, the tool has been in production and is used to determine the transport network for the distribution of spare parts in Germany. One person is dedicated to this task. The exercise is repeated at least once every month, depending on business needs.

The company does not blindly implement the “best” solution returned by the tool. Rather, after a run of the tool the company studies all solutions in the archive by matching each solution against the current operations, infrastructure, capacities, and flows to determine the impact of switching to the new solution on the current distribution setup. This entails checking to which extent the solution can be implemented without too much organizational disruption. Solutions reported in the archive can suggest numerous changes to the current situation, such as switching dealers, or entire milk runs to other transport platforms, shifting supply of a transport platform from one hub to another, eliminating transport platforms altogether, etc. Each of these changes are examined carefully and compared to the potential cost savings in which they result. In this stage, some changes or even some entire solutions proposed by the tool are labeled infeasible because of the large organizational disruption they would cause, regardless of their cost effectiveness. Based on this analysis, the company selects its “best” solution.

The results of such a planning phase, combined with some manual calculations, are used as a guideline for changes in the distribution setup. The tool therefore provides a high-level roadmap on which to base decisions such as which transport platforms to shift to the Czech depot and whether to keep the current transport platforms or switch to new ones. A clearly identifiable decision taken very recently was the closing of a transport platform near the city of Hanover in the north of Germany. Prior to the use of our tool, Toyota was convinced that by closing this expensive platform, it would be difficult to rearrange the distribution network while maintaining service levels. Detailed analysis using our tool showed, however, that this would not be the case and that dealers previously assigned to the closed platform could be integrated in routes starting from other—less expensive—nearby platforms. In practice, this decision turned out to be extremely lucrative, not in the least because no more expensive half-empty line hauls from the depot to this underused transport platform were needed. As predicted by SHORTREC, no decrease in service level was observed. Besides this strategic decision, the assignment of dealers to transport platforms has also been changed several times, and line haul capacity has been optimized each time to reflect the new situation.

As mentioned, the results of the analysis are also used in negotiations with the 3PL providers. On several occasions, Toyota has been able to negotiate a price reduction based on the detailed routing plans provided by SHORTREC.

Another important advantage of the tool is that it can be used to analyze alternative distribution strategies. For example, analysis using the tool showed that direct milk runs from the hubs (without cross docking at a transport platform) are in fact an interesting alternative. Today, Toyota has these kinds of direct milk runs in place at both hubs.

The main benefit of the tool, however, is that it allows Toyota to discover a set of solutions with different structures that they can analyze, and from which they can pick the best one according to their needs. It is of great value that they are not limited to only one “best” solution, but can discover many excellent alternatives in terms of cost saving, capacity saving, increased efficiency, etc., that are totally different in structure. Toyota studies the solutions proposed by the tool in detail and checks the feasibility of their implementation and the effect they would have on the current setup.

Although Toyota is confident that using the tool results in a lower total network cost, the exact cost savings are difficult to quantify. In reality, the total distribution cost is a complex aggregate, influenced by invoicing and price-setting methods, negotiated tariffs, and discounts in different countries with different taxation methods that just cannot be fully reflected by the software. The cost calculations reported by SHORTREC are deemed useful as an approximation of the possible savings that can be achieved, but Toyota does not consider these figures to be exact. However, the flexible cost calculation method of SHORTREC, using a different cost structure per vehicle type, is able to approximate the actual total distribution cost with an acceptable degree of accuracy.

Finally, people at Toyota were also impressed by the advantages of combining the location and routing decisions into a single decision-making tool. “The practical validation of the results generated by this method are strongly facilitated by the use of a very realistic [vehicle-routing] model. This was much more difficult with the high-level tool we had used so far because a lot of assumptions had to be made to put everything in an oversimplified model” (Peeters 2007).

6. Conclusions and Future Research

In this paper, we have discussed the development and implementation of a decision-support tool to facilitate the
design of the transport network for the distribution of spare parts of a large automotive company, Toyota. The underlying method we developed is a tabu search algorithm for a location-routing problem that is used to select 3PL transport platforms out of a relatively large set of potential platforms. The tool developed in this paper is innovative in two ways. First, it generates an archive of structurally diverse solutions. This allows Toyota to react in a faster and more knowledgeable way to changes in the environment and increases its negotiation power toward current and potential 3PL partners. Second, our tool integrates a commercial vehicle-routing solver, which allows for an extremely realistic vehicle-routing subproblem to be modeled and solved.

Several future research points arise. First, several extensions to the underlying model are demanded by Toyota, such as capacity restrictions at the hubs and the introduction of supply flexibility (e.g., a transport platform can be supplied from more than one hub). Second, the changing nature of the 3PL market, as well as volatile demand for spare parts at the car dealers, implies that solutions should be robust with respect to changes in the environment. In the future, we plan to extend our algorithm so that it explicitly evaluates the robustness of the solutions that it produces.

Third, to further decrease the required computation time, more advanced speedup techniques (e.g., quick estimation of route lengths in the vehicle-routing problem) are envisaged. Finally, an extension of the approach to, e.g., the entire European continent, may lead to further cost savings, especially in the areas that might be served from more than one hub. However, local aspects of regional distribution are extremely important in the negotiations with (potential) 3PL partners and should therefore remain among the most important considerations.

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References


