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Multidepot Distribution Planning at Logistics Service Provider Nabuurs B.V.

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Distribution networks of many logistics service providers have evolved from single-depot to complex, dynamic multidepot networks. In a single-depot network, the deliveries from each depot are planned for that depot only, and drivers return to the starting depot to pick up each new order. In a multidepot network, the deliveries from multiple depots can be planned simultaneously; therefore, a logistics service provider can efficiently combine its resources, thus reducing its labor and transport costs. However, an increasing emphasis on reliability, customization, and flexibility is affecting the logistics structures. This paper describes the shift from single-depot planning to multidepot planning for Nabuurs B.V., a large Benelux logistics service provider that implemented a centralized, automated multidepot planning process throughout its organization. We developed a simulation model to evaluate system performance and to address performance challenges. In this paper, we discuss the results of extensive simulation tests and the specific recommendations that Nabuurs B.V. management implemented.

Keywords: multidepot planning; distribution; applications.

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Nabuurs B.V. (Nabuurs in this paper) is a Netherlands-based logistics service provider. Over the past several years, the company has substantially increased its logistics activities, both in the range of services it provides and in the number of countries in which it provides these services. As a result, the transport and distribution network for its ambient products (i.e., dry food and nonfood items) has changed fundamentally; it has evolved from a single-depot (SD) to a multidepot (MD) network. This motivated Nabuurs to implement technological innovations and collaborate with long-term clients; it also impelled the company to create a higher-density network and provided opportunities for efficiency improvements. Companies in the highly competitive logistics service industry must make large investments in return for low profit margins. Because the assets in these networks have become extremely complex, carriers have become less able to control these complexities. As a result, efficient distribution has become increasingly difficult.

In this environment, Nabuurs and the Eindhoven University of Technology collaborated to support decision making at Nabuurs, with a specific focus on the company's transport operations of fast-moving

consumer goods. We started our collaboration by building a quantitative model to provide the company with insights into its transport planning. The performance model we developed had to enable Nabuurs to generate and view the trade-offs of the many desirable performance-related options, including reducing the number of kilometers traveled with empty trucks (i.e., vehicles moving without goods) and the number of trips.

In this paper, we describe research to improve Nabuurs' decision-making processes, with a specific focus on its transport planning. Here, we summarize our analysis and recommendations, which led to significant changes in Nabuurs' operations.

- Our preliminary analysis showed that MD planning provides significant cost savings over SD planning, and these cost savings increase as the order volume grows.

- After comparing and analyzing Nabuurs' current manual planning process, as executed by experienced planners, versus an automated planning support system, ORTEC Transport and Distribution (OTD), we determined that Nabuurs management should upgrade its operational planning tools. These tools can enable

planners to quickly create automated daily planning schedules and easily make manual adjustments when unforeseen situations arise. This utilizes the skills of the planners and the speed of software programs, providing Nabuurs with efficient and effective planning operations. This will also enhance the advantages of multidepot planning, promising significant cost reductions and substantial sustainability improvements in the future.

- When we looked at the planning horizon, the greater part of the incoming order volumes allows efficient and proactive execution of the planning activities. However, the planning activities in Nabuurs occur reactively rather than proactively. Reactive planning refers to a situation in which a company does not plan ahead for problems or opportunities but reacts to them as they happen. In contrast, proactive planning occurs when the company plans ahead to avoid or manage problems. Our preliminary analysis showed that proactive planning gives significant benefits, provided that the order information is received in time. This analysis showed that order arrival times and patterns vary among the clients and that Nabuurs should work with its customers to improve the timely availability of the order information.

Each day, Nabuurs delivers goods from its depots and the depots of its customers to the customers who have placed these orders. In doing so, it faces a common problem—minimizing the costs of distributing these goods, a problem widely known as the vehicle routing problem (VRP). VRP, formulated by Dantzig and Ramser (1959), is a generic name for problems that deal with determining an optimal set of routes to deliver to a number of geographically dispersed customers by using a fleet of vehicles based at one or multiple depots. Although many papers have been published on the classic VRP, only a limited number of papers address the multidepot VRP. Therefore, the scarcity of literature regarding the comparison between SD and MD planning processes is not surprising. Multidepot VRP (MDVRP)—the situation in which a company has multiple depots from which it can serve its customers—is an extension of the VRP. If the customers are clustered around these depots, the distribution problem can be modeled as a set of independent VRPs. However, if the customers and the depots are dispersed geographically, it should

be modeled as an MDVRP. In addition to addressing the typical VRP decisions, an MDVRP requires the assignment of customers to depots and a fleet of vehicles to each depot. The general objectives of the MDVRP are to minimize the number of vehicles in a fleet and the travel time of these vehicles. Moreover, the demand of customers can be served from multiple depots. In the pickup-and-delivery problem (PDP), each transportation request specifies a single origin and a single destination and all vehicles depart from and return to the depot. PDPs must also satisfy precedence relationships between requests and customers. Desaulniers et al. (2002), Parragh et al. (2008), and Berbeglia et al. (2010) provide extensive surveys of PDPs. In our study, we formulate Nabuurs' transportation system as a heterogeneous multidepot PDP with time windows and company-specific driver's rule constraints. Appendix A shows the mathematical model formulation.

We organized the remainder of this paper as follows. In the *About Nabuurs* section, we introduce Nabuurs and its current distribution planning system. The *Problem Description and Analysis* section provides a detailed explanation of the current challenges based on our preliminary analysis. *Design of an Automated Multidepot Planning System* explains our proposed methods to address these challenges. In *Results*, we then discuss the results of extensive computational experiments and include managerial insights. We discuss our conclusions in *Conclusions and Future Outlook*. Finally, the appendices describe the mixed-integer programming model and the algorithms used in our simulation model.

About Nabuurs

Headquartered in Haps, the Netherlands, Nabuurs was founded in 1962 by Jacques Nabuurs. Starting with one truck for transporting live poultry, the company has grown to be 13th in the top 50 logistics service providers in the Netherlands. It has an annual turnover (i.e., sales revenue) of more than 100 million euros and operates over 170,000 square meters of warehouses in the Netherlands, Belgium, Germany, and Poland. The family business, directed by Tjebbe and Ard Nabuurs, employs more than 1,000 people (Nabuurs 2013). Nabuurs focuses on transportation planning (i.e., cost, service, sustainability) for its customers' products.

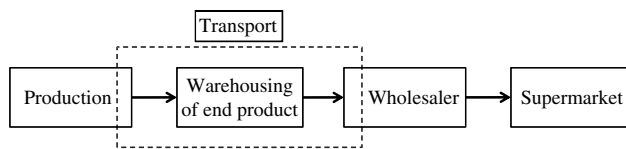


Figure 1: Transportation activities in which Nabuurs is involved are depicted in the supply chain network for refrigerated, frozen, and ambient products—its three market segments.

Its clients include H. J. Heinz, FrieslandCampina, SCA Hygiene Products, and Refresco.

Outside the Netherlands, transport is Nabuurs' core activity; within the Netherlands, both transport and warehousing are its major businesses. Nabuurs provides services in three market segments: refrigerated, frozen, and ambient products (see Figure 1).

The refrigerated market segment includes refrigerated products, for which Nabuurs offers distribution services for the retail and wholesale sectors. To maintain the conditions these products require, its trucks and warehouses are equipped with temperature control systems. In the frozen market segment, Nabuurs addresses all the distribution, storage, and picking requirements of its clients.

"Ambient" is a term used within the food and beverage industry to describe products (or storage of such products) that require only an ambient temperature (i.e., room temperature). The ambient market segment covers both food and nonfood products, such as soft drinks, biscuits, cereals, tinned meat, tinned fruit, rice, and pasta. This market segment provides the largest share of revenue to Nabuurs and requires more trucks and employees than either of the other market segments. The implementation we discuss in this paper focuses exclusively on the logistics operations of ambient products.

Problem Description and Analysis

The planning process at Nabuurs is centrally controlled using a planning support system, OTD. OTD controls a dynamic and complex multidepot network. However, its responses to planning requirements are usually reactive rather than proactive; in addition, because OTD is a manual system, it hinders the planning process.

In the following sections, we give a detailed analysis of the current processes, structure, and performance of the transport and distribution activities within Nabuurs' ambient product transport network. We follow the process, control, and information model of Bemelmans (1986). This framework provides a structured analysis approach from the perspective of improving the corresponding planning and control structure. Bemelmans assumes that the primary process of an organization determines the type of control required; therefore, its information structure results from the control structure adopted.

Process and Service

We define a process as a method or system. For Nabuurs, this is mainly the execution of logistics services to reduce travel time and distance within its transport and distribution network. Nabuurs is positioned in the center of the supply chain, which executes three types of services: (1) transport between a production location and (or) a distribution center (DC), (2) warehousing, and (3) transport and distribution to a wholesaler or customer (e.g., Refresco). Nabuurs' central position in the supply chain can be considered as dependent. However, this can be a competitive advantage because it allows the company to build and maintain long-term relationships with its clients. Moreover, a logistics service provider can foster a strong partnership with a client by assuming responsibility for that client's entire transport and warehousing activities.

Control and Structure

The entire transport and distribution planning process for the ambient market segment is centrally controlled from a Nabuurs office in Ede, the Netherlands; however, it is supervised from an office in Haps, the Netherlands.

The planning process addresses the control of the depots, transport flows, resources, and level of planning tasks. For the ambient market, loading sites of discharge locations are often production locations of long-term clients and (or) DCs. Any process to improve distribution planning must consider these loading and unloading locations.

Ghani et al. (2013) categorize transportation planning tasks into three levels—strategic, tactical, and operational (see Figure 2). The relationship between the operational and tactical levels is particularly important for our research.

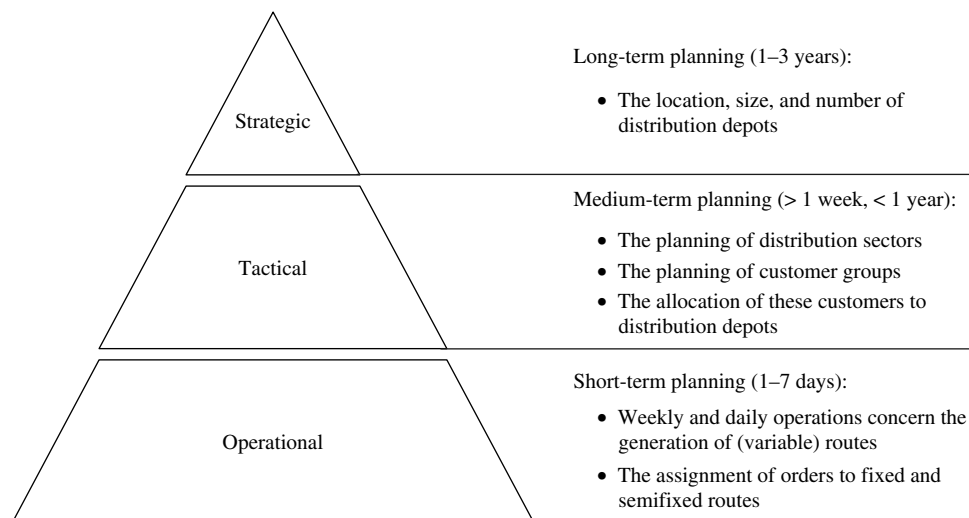


Figure 2: Nabuurs' transportation decisions are based on hierarchical planning levels.

Information and Performance

According to Bemelmans (1986), information serves as a resource for several control and decision processes. We can look at information from two perspectives: functionality and performance. To support the transport activities in the ambient market segment, various information technology (IT) systems—including Microsoft Office, the data warehouse, and OTD—provide information; Nabuurs' IT systems are also directly linked to client warehouse management and enterprise resource planning (ERP) systems. Performance indicators within the network determine when the information must be produced. Using a planning support system (e.g., OTD) can reduce costs and improve service levels. OTD considers all the factors and conditions that are important within the specific organization or branch. However, this planning tool must be considered as an addition to the ERP and (or) transport management system that support(s) the planner.

Design of an Automated Multidepot Planning System

Nabuurs did not optimally use OTD for several reasons. First, its planning processes were still manual, principally because of problems with OTD settings; these problems relate to truckers who spend the night in their trucks. Because a majority of Nabuurs' drivers

only stay overnight between shifts, these problems impeded effective MD planning. A driver who is asked to stay overnight must receive additional compensation. Second, Nabuurs lacked clear performance measurements and required more knowledge about the quantitative factors (e.g., travel time, kilometers traveled) and qualitative factors (e.g., driver flexibility, availability) that affect these measurements. For example, the company did not have precise information on the performance per delivery (e.g., the ratio between the number of kilometers traveled by empty trucks and the number of KMs traveled by trucks with full loads). Third, simulating network changes was difficult and time consuming. For example, in responding to a tender, Nabuurs might want to determine and quantify the additional efficiencies it could obtain by implementing a more efficient route-planning process. To address these issues, we designed our study with three objectives: (1) to design a model to verify whether, for the current network of the ambient market segment, an MD operating process would be more cost efficient than an SD process; (2) to determine the benefits of automated MD planning over manual planning; and (3) to implement the model to calculate the effects of changing volumes and (or) adding or deleting clients.

Based on our analysis of the processes, control mechanisms, and the information available, we generated a detailed cause-and-effect diagram (Ishikawa and

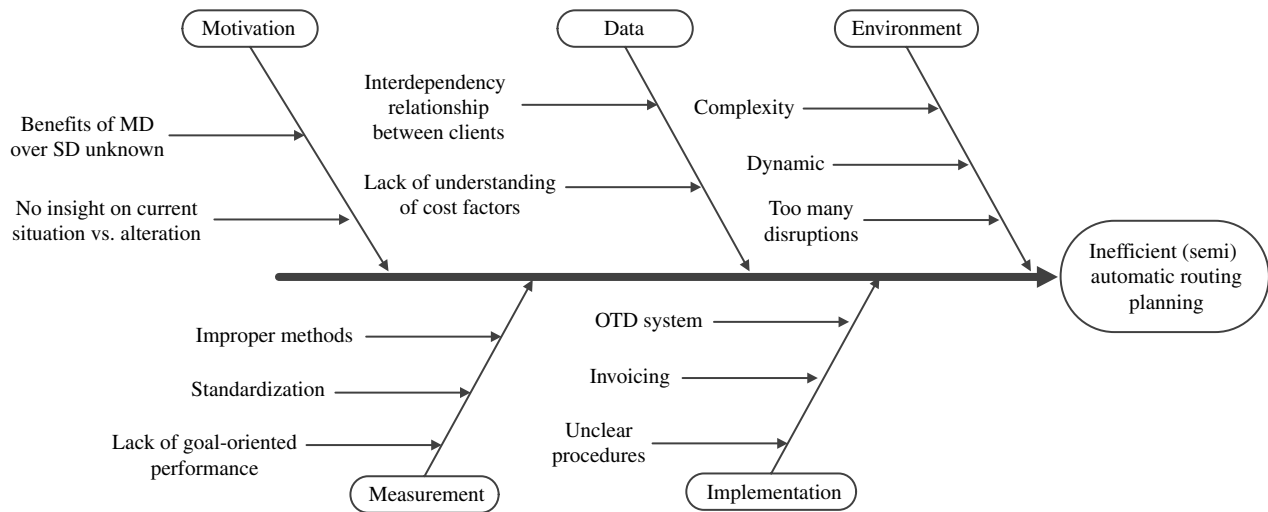


Figure 3: The cause-and-effect diagram shows an inefficient, semiautomatic route-planning process.

Loftus 1990) (see Figure 3) of Nabuurs' route-planning process.

Improving route planning and reducing logistics costs by more efficiently executing the planning processes must be an ongoing objective. The right side of Figure 3 shows the main objective, an efficient (i.e., semiautomatic) route-planning system for daily use. We determined that this objective would be feasible if Nabuurs implemented the following three recommendations: (1) completion and implementation of OTD changes, (2) improvement of the current planning process, and (3) adoption of a consistent invoicing policy.

Because the first recommendation depends on external factors, we could not include it in our study. However, the time needed for replanning the transport requests requires calculations and improvements that involve complex solutions; this is impracticable without automated planning support. The Nabuurs network may benefit from an automated route-planning process, whether Nabuurs uses the process in daily planning or merely for performance measurement and (or) scenario analysis. If this recommendation cannot be performed within OTD, Nabuurs should reconsider OTD's implementation.

We also omitted the third requirement from our scope of work because it is based on profits, margins, and exception handling rather than on bottom-line

costs. Improving the daily planning process requires a new invoicing policy. Nabuurs should implement a consistent tariff structure that clearly defines what each party pays and appropriately divides the cost savings and corresponding profits.

Based on the cause-and-effect diagram in Figure 3, the objective of our design is to build a model (1) to substantiate that an MD operating process is more cost effective than an SD operating process in the current network, and (2) to quantify the benefits of changing from an SD process to an MD process. We implemented the model to calculate the effects of adding (deleting) clients and of increasing (decreasing) volumes on the costs of the network. Therefore, we divided the design phase into two phases, as follows.

- Phase 1: We developed a performance evaluation model (PEM) to calculate and visualize the network performance by means of the kilometers driven by empty trucks and the kilometers traveled by trucks with full loads.

- Phase 2: We developed and implemented a simulation model, which we based on ORTEC's tool, SHORTREC. This tactical tool provides insights into the routing decisions to allow the user to minimize total costs.

Phase 1: The Performance Evaluation Model

Measuring the performance (i.e., the number of kilometers traveled by empty trucks versus the number

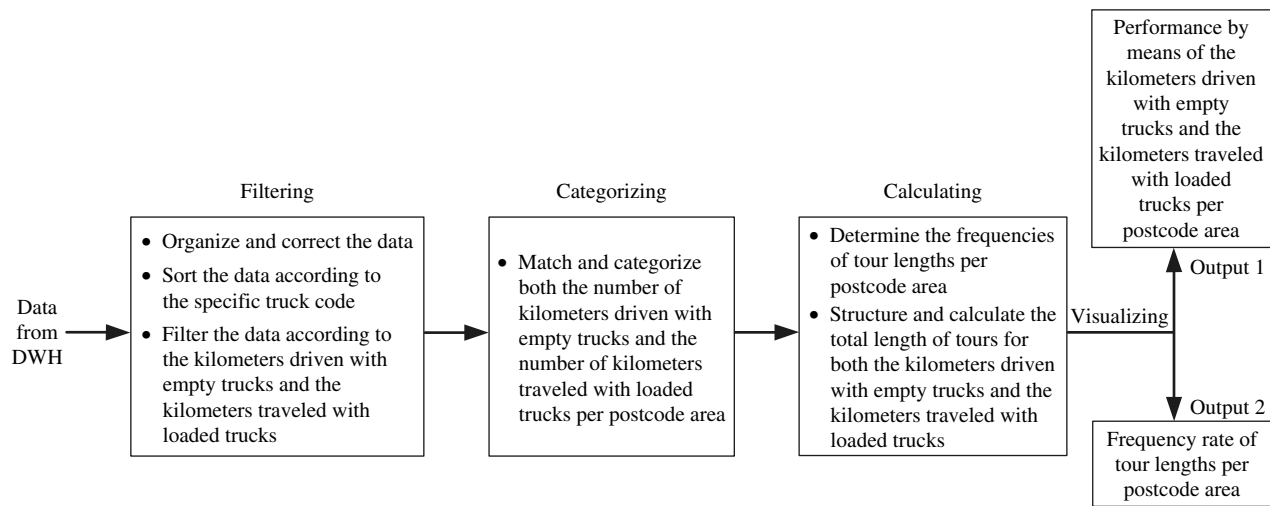


Figure 4: The diagram shows an overview of the PEM.

traveled by fully loaded trucks) within the network is imperative. At the time of our study, (1) the network did not include any substantial performance measurements, and (2) a tool to evaluate the expected performance did not exist. Figure 4 shows an overview of the PEM we used, including the input (i.e., data from the data warehouse (DWH)), process, and output variables.

The PEM has three building blocks; they (1) filter the input data, (2) run a Visual Basic program for categorization, and (3) run calculations to allow the user to visualize the output.

Because the accuracy of the PEM's results is critical, we assessed the construct validity, which we define as the extent to which a tool measures what it is intended to measure (Groot 1969). We achieved construct validity by discussing the filtering scenarios and results with the Nabuurs staff members responsible for the transport network. Using the methodology of Sargent (2005), we used real data (i.e., the data used for invoicing), which we obtained from the DWH, for our model.

Phase 2: The SHORTREC-Based Simulation Model

We use simulation to describe and analyze a system's behavior, allow a user to ask what-if questions about the live system, and aid in the systems design process (Banks 1999). After developing the PEM, we had to construct the simulation model to (1) obtain insights about situations in which MD planning is more advantageous

than SD planning and (2) compare networks in which changes have been made to previous and (or) potential (i.e., future) versions of that network. To implement our design, we constructed a simulation model, SHORTREC, a tactical tool that meets all three objectives, as we discuss at the beginning of this section.

We designed SHORTREC to minimize overall costs. The solution methodology starts with a basic solution and then tries to improve on that solution by running optimization routines multiple times. This is clearly a time-intensive process, especially when many alternatives are possible. SHORTREC includes both construction and improvement algorithms, indicating the versatility of its optimization possibilities (see Table 1). Appendix B provides additional details of these algorithms.

Construction algorithms	Improvement algorithms
Sequential insertion algorithm	Optimization algorithms
Savings algorithm	Cyclic transfer algorithm
Priority-based parallel insertion algorithm	Tabu search algorithm
Cluster-based insertion algorithm	
Multidepot insertion algorithm	
Group-based insertion algorithm	
Pickup-and-delivery insertion algorithm	

Table 1: The table categorizes the two types of algorithms—construction and improvement—used by SHORTREC, and lists the algorithms in each category.

Several studies, including Quak and de Koster (2006), Kant et al. (2008), and Schittekat and Sørensen (2009), discuss SHORTREC. Sargent (2005) defines verification of a (computerized) model as ensuring that the computer programming and implementation of the conceptual model are correct. The verification step checks whether the model has been built correctly and functions as it should. We validated our results and then discussed them with staff members in Nabuurs' planning department. Based on our validations and staff comparisons, we concluded that SHORTREC is able to meet the above-stated objectives and requirements and is a viable tool for performing scenario analysis.

Results

In this section, we discuss the results of the PEM and scenario analysis. In response to Nabuurs' lack of knowledge about performance within particular postcode areas, which often include multiple unloading locations, we developed the PEM to evaluate existing activities. Outputs include (1) maps that show the ratios between the number of kilometers traveled with trucks empty and the number traveled with loaded trucks and (2) frequency diagrams that show trip lengths (see Figure 5).

To determine whether the network changes affected performance positively or negatively, we performed a

series of tests, which we subdivided into the following three scenarios:

- Scenario 1: SD versus MD planning.
- Scenario 2: MD (manual) versus MD (automated) planning.
- Scenario 3: Reactive versus proactive planning.

Scenario 1: SD vs. MD Planning

In Scenario 1, we compare SD and MD planning processes for the ambient market network. Our objective is to verify the quantitative savings achieved by using the MD operating process. By representing the route planning of a particular driver, we can validate the savings that can be achieved by using a MD setting (versus a SD setting).

We use one day of real orders, which initially contains 174 orders. We first reduce the number of orders and then generate four subscenarios, which we base on Scenario 1, by deleting the 74 orders with the largest volume and the 74 orders with the least volume. The remaining changes we make in SHORTREC concern the number of available preloaded vehicles and the vehicle fixed price used. The number of available preloaded vehicles is adjusted to the number of orders (i.e., one-seventh of the total number of orders), and the vehicle fixed price is set to 100 euros in the simulation. Table 2 shows the settings we use and the resulting key performance indicators (KPIs).

First, we can conclude from Table 2 that cost savings diminish as the number of orders decreases. Second, we can see that the number of available preloaded vehicles affects the comparison between SD and MD planning. Therefore, based on these findings, using a minimum number of preloaded vehicles is appropriate. Finally, we observe that deleting the smallest orders results in greater cost savings than deleting the largest orders; for example, deleting 10 small orders has a lesser effect on the total order volume than deleting 10 large orders. Therefore, a larger order volume yields higher cost savings than a smaller order volume. We also note that driver waiting time varies in the various scenarios. Because drivers are paid for waiting time, its impact is outside the scope of our research. However, this could be a topic for future research.

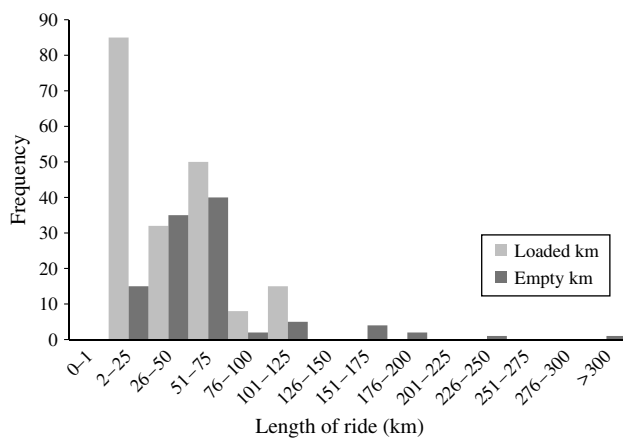


Figure 5: For postcode 34, this figure illustrates the number of kilometers traveled by fully loaded vehicles ("Loaded km") and the number of KMs traveled by empty trucks ("Empty km").

Scenario 1				Performance comparison							
Setting	No. of orders	Smallest or largest volume orders deleted	No. of available preloaded vehicles	Cost (€)	Distance (km)	No. of vehicles	No. of trips	Working time (min.)	Driving time (min.)	Stopping time (min.)	Waiting time (min.)
SD	174	0	25	27,693	21,803	57	116	34,392	18,932	14,280	1,339
MD	174	0	25	25,267	19,287	54	119	31,836	17,117	14,280	199
Difference (%)				−8.76	−11.54	−5.26	2.96	−7.43	−9.69	0.00	−85.14
SD	100	−74 large	25	11,292	8,856	34	49	13,838	7,887	5,880	71
MD	100	−74 large	25	11,229	8,595	30	50	13,842	7,690	5,880	212
Difference (%)				−0.56	−2.95	−11.76	2.04	0.03	−2.50	1.02	198.59
SD	100	−74 large	10	12,853	9,919	30	48	15,576	8,657	6,720	199
MD	100	−74 large	10	12,802	9,868	28	50	15,643	8,623	6,840	180
Difference (%)				−0.40	−0.51	−6.67	4.17	0.43	−0.39	1.79	−9.55
SD	100	−74 small	25	19,183	15,206	46	96	24,096	13,237	10,140	719
MD	100	−74 small	25	18,404	14,465	41	96	23,075	12,697	10,140	238
Difference (%)				−4.06	−4.87	−10.87	0.00	−4.24	−4.08	0.00	−66.90
SD	100	−74 small	10	21,252	17,173	47	96	25,883	14,763	11,040	80
MD	100	−74 small	10	19,892	15,563	43	96	25,081	13,567	11,100	414
Difference (%)				−6.40	−9.38	−8.51	0.00	−3.10	−8.10	0.54	417.50

Table 2: The table presents an overview of the tests we did to compare SD and MD planning.

Scenario 2: MD (Manual) vs. MD (Automated) Planning

In Scenario 2, we compare the current manual planning process to an automated planning process. This comparison validates the application of SHORTREC for the ambient market segment (see Table 3).

The total costs of manual planning are the amount that Nabuurs charges the client minus the profit that the company generates. However, we cannot know whether actual planning results in higher or lower costs than the estimated costs. Nevertheless, our comparison focuses on the planning methods (i.e., manual and automatic)—not the execution of the planning, which is difficult to measure because of uncertainty in real traffic conditions and freight demand. Based on the

KPI results in Table 3, we see that cost savings of eight percent are achieved by decreasing the number of KMs driven and the working time. In addition, the number of vehicles increases, but the number of trips remains the same. The cost savings are primarily the result of fewer kilometers driven with empty trucks, mainly because SHORTREC combines the depots, orders, and drivers in a more intelligent and interchangeable manner. Executing a SHORTREC solution for this small number of orders takes only a few minutes, instead of several hours as the manual planning process requires. However, small reactive changes (e.g., a slight increase in the time window) are easily applicable to the manual planning process; therefore, in such situations, using SHORTREC is unnecessary. For example, in the

Scenario 2	Cost (€)	Distance (km)	No. of vehicles	No. of rides	No. of orders	Working time (min.)	Driving time (min.)	Stopping time (min.)	Waiting time (min.)
Manual	5,643	5,083	10	32	32	7,945	N/A	N/A	N/A
SHORTREC	5,191	4,451	11	32	32	6,567	3,933	2,445	189
Difference (%)	−8.01	−12.43	10.00	0.00	0.00	−17.34			

Table 3: The table shows a comparison of the KPIs in the MD manual and automated scenarios (SHORTREC).

manual planning process, 10 vehicles can be used; no SHORTREC solution allows this. We conclude that because SHORTREC provides insights about best route combinations, it can support the current planning process.

Scenario 3: Reactive vs. Proactive Planning

In Scenario 3, we highlight the differences between reactive and proactive planning. Proactive planning can provide benefits (e.g., by allowing changes to the departure locations of a vehicle fleet); however, it is possible only if the order information is received in time. Therefore, we assume that the order information is available beforehand (i.e., 48 hours). In Nabuurs, only a small number of the orders meets this requirement.

Because a depot within the network contains its own specific types of products, the current manual planning process, which is performed per DC, is viable. Reactive planning does not provide any insights about upcoming orders. This reactive planning procedure, as currently used, is a logical method for dealing with this complex and uncertain environment, although a proactive approach would improve the planning process and provide a benefit for the drivers.

Table 4 shows the KPI results of the reactive and proactive process comparison.

To simulate these two types of planning, we define free end location as allowing a driver to end a trip at a depot other than the depot from which he (she) departed. We define free start location as allowing a driver to select the start location. However, if a reactive daily planning schedule is generated (i.e., the planning process does not provide information about the next day's orders), a start location may be random; the

driver cannot select a desirable start location. Note that the total break time for reactive and proactive planning are found to be 0 and 72 hours, respectively. Using proactive planning, the total costs are €20,447 when nine drivers (72 hours' waiting time, with an 8-hour rest per driver) are scheduled with a one-night rest. The results show a cost improvement of 14.77 percent for planning with a time horizon of 48 hours and 100 orders per day. In addition, this solution requires six fewer vehicles than the reactive planning solution does. Because more than 150 orders are transported over the network each day, annual cost savings resulting from using a proactive planning procedure are large. Nevertheless, to do a reliable comparison, we must select an appropriate reactive planning model. Because Nabuurs can request that the majority of the drivers take a one-night rest within their vehicles, we can define two scenarios for modeling reactive planning—one scenario as an upper-bound solution and the second as a lower-bound solution. Table 5 shows the upper- and lower-bound solutions, which are based on reactive planning of two separate days with 100 orders a day (i.e., 48 hours and 200 orders).

Although the first solution (see Table 5) more correctly models reactive planning, it does not consider the advantages of a one-night rest. The second solution includes advantages for drivers and for Nabuurs: drivers can select free start and free end locations; because Nabuurs does not consider (or pay for) a one-night rest as working hours, the driver may choose his destination. Therefore, based on the aforementioned descriptions, we conclude that the following scenario for modeling reactive planning is the most beneficial: reactive planning with a free start location on the first

Scenario 3				Performance and comparison							
Horizon: 48 hours	Option for night's rest	Option for free end location	Option for free start location	Cost (€)	Distance (km)	No. of vehicles	No. of rides	Working time (min.)	Driving time (min.)	Stopping time (min.)	Waiting time (minutes)
Reactive planning: 48 hours (2 × 24)	No	Yes	Yes	23,989	17,155	62	133	29,752	15,317	13,005	1,430
Proactive planning: 48 hours	Yes	Yes	Yes	20,447	13,399	56	130	26,897	11,827	17,040	2,350
			Difference (%)	−14.77	−21.89	−9.68	−2.26	−9.60	−22.79	31.03	64.34

Table 4: The table provides detailed results of the reactive and proactive MD ambient planning scenarios.

Solutions	Option for one-night rest in vehicle	Option for free end location	Option for free start location	Cost (€)	Distance (km)	No. of vehicles	No. of rides	Working time (min.)	Driving time (min.)	Stopping time (min.)	Waiting time (min.)
Upper-bound	No	No	No	31,589	25,063	66	131	37,226	21,972	13,680	1,574
Lower-bound	No	Yes	Yes	20,349	13,442	55	128	26,412	11,868	12,720	1,824

Table 5: The table shows upper- and lower-bound solutions for reactive planning.

day and a free end location on the second day. This solution precludes the night-rest issue and includes the advantages of a free start and free end location.

Practical Implications

Based on the potential benefits our study shows, as we summarize next, Nabuurs decided to improve its current planning system (OTD).

- In all the cases we tested, we achieved cost savings by switching from an SD to an MD process; additional cost savings accrued as order volumes increase.

- In Scenario 2, when we compared automated SHORTREC planning and the current manual planning process using the same number of orders, we achieved cost savings of eight percent by combining depots, orders, and drivers to make them more interchangeable. Although small reactive changes are easier to apply to the manual planning process, an automated SHORTREC solution for this small number of orders takes only a few minutes, instead of the several hours required for manual planning.

- In Scenario 3, using 200 orders and a time horizon of 48 hours, the proactive planning approach reduces costs by 14.77 percent and uses six fewer vehicles than the reactive planning approach.

- SHORTREC is a viable tool for supporting current planning on a tactical rather than operational level. The planning system can generate rapid route combinations and allow planners to do what-if analysis for planning purposes.

Conclusions and Future Outlook

Our research allowed us to gain insights into multidepot distribution networks, and our results demonstrate the benefits of applying operations research in freight transportation and logistics.

This research convinced Nabuurs management to make two important investments: first, it decided

to upgrade OTD, its operational planning tool. This upgraded support allows the planners to quickly and easily create automated daily planning schedules and make manual adjustments to the schedules when unforeseen situations arise. Second, Nabuurs implemented the tactical planning tool SHORTREC. Although using advanced network analyses had been a company goal for some time, Nabuurs considered such analyses to be too time consuming. Our research showed that SHORTREC performs faster, particularly in response to network changes. It provides Nabuurs with a useful system for tactical planning activities, such as advanced analyses using distribution and transportation scenarios.

In our recommendations, which are based on the results we obtained in our study, we advised Nabuurs to focus on the following: (1) change its planning process from reactive to proactive, (2) use automated planning to provide improved solutions to complex problems, and (3) measure and evaluate transport network performance.

Appendix A. Mathematical Formulation

In this appendix, we describe the mathematical formulation of the heterogeneous fleet multidepot pickup and delivery problem with time windows and company-specific driver's rule constraints. The mathematical formulation we present here is an extension of Desaulniers et al. (2002) and Ropke and Pisinger (2006), and it is tailored for the transportation requirements of Nabuurs. Let us first introduce the indices, parameters, and variables.

Indices

- $\mathcal{P}$: Set of pickup nodes, $\mathcal{P} = \{1, \dots, n\}$.
- $\mathcal{D}$: Set of delivery nodes, $\mathcal{D} = \{n+1, \dots, 2n\}$.
- $\mathcal{N}$: Set of pickup and delivery nodes, $\mathcal{N} = (\mathcal{P} \cup \mathcal{D})$.
- $\mathcal{K}$: Set of all vehicles, $\mathcal{K} = \{1, \dots, k\}$.
- $\mathcal{M}$: Set of start terminals of vehicles, $\mathcal{M} = \{m_1, \dots, m_k\}$.
- $\mathcal{M}'$: Set of end terminals of vehicles, $\mathcal{M}' = \{m'_1, \dots, m'_k\}$.
- $\mathcal{V}$: Set of all locations, $\mathcal{V} = (\mathcal{N} \cup \mathcal{M} \cup \mathcal{M}')$.

- $\mathcal{A}$: Set of ordered pairs of nodes (i.e., arcs)
 $\mathcal{A} = \{(i, j): i, j \in \mathcal{V}, i \neq j\}$.
 $\mathcal{G}$: A complete undirected graph, $\mathcal{G} = (\mathcal{V}, \mathcal{A})$.
 $\mathcal{P}_k$: Set of pickup nodes that can be served by vehicle k ,
 $\mathcal{P}_k = \{1, \dots, n_1\}$ and $n_1 \leq n$.
 $\mathcal{D}_k$: Set of delivery nodes that can be served by vehicle k ,
 $\mathcal{D}_k = \{n+1, \dots, n+n_1\}$ and $n_1 \leq n$.
 $\mathcal{N}_k$: Set of pickup and delivery nodes $\mathcal{N}_k = (\mathcal{P}_k \cup \mathcal{D}_k)$.
 $\mathcal{K}_i$: Set of vehicles that can serve request i $\mathcal{K}_i = \{1, \dots, k_1\}$
and $k_1 \leq k$.
 $\mathcal{V}_k$: Set of all nodes that can be visited by vehicle k
 $\mathcal{V}_k = (\mathcal{N}_k \cup \mathcal{M}_k \cup \mathcal{M}'_k)$.
 $\mathcal{A}_k$: Set of ordered pairs of nodes for vehicle k
 $\mathcal{A}_k = \{(i, j): i, j \in \mathcal{V}_k, i \neq j\}$.
 $\mathcal{G}_k$: A complete undirected subgraph $\mathcal{G}_k = (\mathcal{V}_k, \mathcal{A}_k)$.

Parameters

- Q_k : Capacity of vehicle k ($k \in K$).
 $\mathcal{T}_1$: Maximum driving time on any arc (i, j) (in seconds).
 $\mathcal{T}_2$: Maximum route time (in seconds).
 $\bar{v}^r$: R nondecreasing speed levels ($r = 1, 2, \dots, R$).
 c_r : Fuel cost at a speed level r per kilometer ($r \in \mathcal{R}$).
 c_{ij}^k : Other travel-related costs between nodes i and j using
vehicle k ($k \in \mathcal{K}, (i, j) \in \mathcal{A}$).
 d_{ij} : Distance between nodes i and j ($i, j \in \mathcal{A}$).
 l_{ij} : Minimum speed level between nodes i and j ($i, j \in \mathcal{A}$).
 a_i : A lower bound on the time window of customer i
($i \in \mathcal{V}$).
 b_i : An upper bound on the time window of customer i
($i \in \mathcal{V}$).
 t_i : Service time of customer i ($i \in \mathcal{P} \cup \mathcal{D}$).
 q_i : A nonnegative demand for every i ($i \in \mathcal{P}$).

Variables

- x_{ij}^k : A binary variable equal to 1 if arc (i, j) is used by
vehicle k and 0 otherwise ($k \in \mathcal{K}, (i, j) \in \mathcal{A}$).
 S_j^k : The time at which service starts at node j with
vehicle k ($k \in \mathcal{K}, j \in \mathcal{V}$).
 O_j^k : The time spent on a route that has a node j as last
visited before returning to the depot with vehicle k
($k \in \mathcal{K}, j \in \mathcal{V}$).
 L_j^k : Amount of load at node j on vehicle k ($k \in \mathcal{K}, j \in \mathcal{V}$).
 w_{ij}^r : A binary variable equal to 1 if arc (i, j) is traversed at
a speed level r and 0 otherwise ($(i, j) \in \mathcal{A}, r \in \mathcal{R}$).

An integer linear programming formulation is shown as follows:

$$\text{minimize } \left\{ \sum_{r \in \mathcal{R}} c_r \sum_{i, j \in \mathcal{A}_k} d_{ij} w_{ij}^r \right. \quad (1)$$

$$\left. + \sum_{k \in \mathcal{K}} \sum_{i, j \in \mathcal{A}_k} c_{ij}^k x_{ij}^k \right\} \quad (2)$$

subject to

$$\sum_{k \in \mathcal{K}_i} \sum_{j \in \mathcal{N}_k} x_{ij}^k = 1 \quad \forall i \in \mathcal{P}, \quad (3)$$

$$\sum_{j \in \mathcal{N}_k} x_{ij}^k - \sum_{j \in \mathcal{N}_k} x_{j, n+i}^k = 0 \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{P}_k, \quad (4)$$

$$\sum_{j \in \mathcal{N}_k} x_{m_k, j}^k = 1 \quad \forall k \in \mathcal{K}, \quad (5)$$

$$\sum_{i \in \mathcal{N}_k} x_{i, m'_k}^k = 1 \quad \forall k \in \mathcal{K}, \quad (6)$$

$$\sum_{i \in \mathcal{V}_k} x_{ij}^k - \sum_{i \in \mathcal{V}_k} x_{ji}^k = 0 \quad \forall k \in \mathcal{K}, \forall j \in \mathcal{N}_k, \quad (7)$$

$$S_i^k + t_i + \sum_{r \in \mathcal{R}} d_{ij} w_{ij}^r / \bar{v}^r + M_{ij}^k (1 - x_{ij}^k) \leq S_j^k \quad \forall k \in \mathcal{K}, \forall (i, j) \in \mathcal{A}_k, \quad (8)$$

$$a_i \leq S_i^k \leq b_i \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{V}_k, \quad (9)$$

$$S_i^k \leq S_{n+i}^k \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{P}_k, \quad (10)$$

$$S_j^k + t_j + \sum_{r \in \mathcal{R}} d_{j0} w_{j0}^r / \bar{v}^r - F(1 - x_{j0}^k) \leq O_j^k \quad \forall k \in \mathcal{K}, \forall j \in \mathcal{A}_k, \quad (11)$$

$$L_i^k + q_i + W_{ij}^k (1 - x_{ij}^k) \leq L_j^k \quad \forall k \in \mathcal{K}, \forall (i, j) \in \mathcal{A}_k, \quad (12)$$

$$L_i^k \leq Q_k \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{V}_k, \quad (13)$$

$$\sum_{r \in \mathcal{R}} d_{ij} w_{ij}^r / \bar{v}^r \leq \mathcal{T}_1 \quad \forall (i, j) \in \mathcal{A}, \quad (14)$$

$$O_j^k \leq \mathcal{T}_2 \quad \forall k \in \mathcal{K}, \forall j \in (\mathcal{N}_k), \quad (15)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall k \in \mathcal{K}, \forall (i, j) \in \mathcal{A}_k, \quad (16)$$

$$w_{ij}^r \in \{0, 1\} \quad \forall (i, j) \in \mathcal{A}, r = 1, \dots, R, \quad (17)$$

$$S_i^k; L_i^k; O_i^k \geq 0 \quad \forall k \in \mathcal{K}, \forall i \in \mathcal{V}_k. \quad (18)$$

The objective function (1) and (2) minimizes the total cost of routing. It consists of two components—the speed-related fuel cost and the other travel-related cost. Constraints (3) state that each pickup location must be visited. Constraints (4) ensure that a vehicle visits the delivery location after it has visited the pickup location. Constraints (5)–(7) ensure that each vehicle k starts from its start depot and terminates its route at its terminal depot. Constraints (8), (11), and (12) are linearized, as in Cordeau (2006). Constraints (8), where $M_{ij}^k = \max\{0, b_i + t_i + d_{ij}/l_{ij} - a_j\}$, enforce the time-window restrictions. We also assume that $t_{i, n+i} + t_i > 0$. Constraints (10) force the vehicle k to visit a pickup node first. Constraints (11), where F is a large number, also enforce the time-window restrictions. The time between nodes i and j also holds the triangular inequality: $t_{ij} \leq t_{il} + t_{lj}$ for all $i, j, l \in \mathcal{V}$. Constraints (12) and (13) are the load constraints, where $W_{ij}^k = \min\{Q_k, Q_k + q_i\}$. Constraints (14) ensure that driving time between nodes i and j must be less than $\mathcal{T}_1$. Constraints (15) ensure that total route time must be less than $\mathcal{T}_2$.

Appendix B. Algorithms

In this appendix, we present the SHORTREC algorithms. The information originates from ORTEC documents and presentations. Below, we enumerate all the algorithms included in SHORTREC and clarify them in a summary.

Construction Algorithms

The construction algorithms build initial feasible solutions without trying to optimize them. In construction algorithms, two criteria play a central role: (1) the selection criterion (i.e., which order should be selected, given the current solution) and (2) the insertion criterion (i.e., where should the selected order be inserted). The goal of construction methods is to produce a feasible initial solution that can be improved upon later by means of improvement methods.

- The sequential insertion algorithm (SIA): Trips are constructed sequentially, where all vehicles are empty initially. The most important step in this algorithm is the selection of the first order (seed) in a vehicle. The order farthest from the depot is usually chosen as the seed. Other possibilities for the seed are the largest order and the order with the smallest time window. When the seed is selected, orders are added to the vehicle until the vehicle is full. Therefore, a vehicle is selected and filled with orders until no more orders can be feasibly added. Then, a second empty vehicle is selected and the procedure is repeated until a predefined number of iterations completes.

- The savings algorithm (SA): The savings method by Clarke and Wright (1964) is one of the most widely known heuristics. The algorithm starts with a solution in which each order is supplied by a separate trip and each trip by a separate vehicle. Then the savings (e.g., distance saved by combining trips) are calculated and the feasible trips with maximum savings are iteratively selected to form the initial solution. In the SA, the trips are constructed simultaneously.

- The priority-based parallel insertion algorithm (PbPIA): The PbPIA groups orders based on restrictions between orders and vehicles. It starts by constructing a matrix, the difficulty matrix, in which it stores feasible vehicles for each order and the row and column totals of the matrix. In each step of the algorithm, a group of orders and vehicles that should be scheduled is selected. That is, in each step of the algorithm, small subproblems are constructed and solved using the SIA.

- The cluster-based insertion algorithm (CbIA): The steps of the CbIA are similar to the steps of the SIA and can be summarized as follows: (1) select the seed order, (2) find a vehicle for the seed, (3) add orders to the selected vehicle until the vehicle is full, (4) find a cheaper vehicle, and (5) if orders remain, go to step 1. The algorithm starts by determining the difficulty and the cluster size of the orders. An order's difficulty is determined by the number of allowed vehicles and depots. The cluster size is the number of orders within a prespecified radius from each other.

- The multidepot insertion algorithm (MDIA): In step 1 of the MDIA, the sort method is selected. In step 2, after all necessary data have been initialized, the seed order is selected based on difficulty (i.e., based on the number of depots and vehicles). In step 3, the largest remaining empty vehicle is selected; in step 4, orders are added to the vehicle based on the selected sort method. If no more orders can feasibly be added to the vehicle and orders remain, the procedure is repeated starting at step 2.

- The group-based insertion algorithm (GbIA): In the GbIA, the orders are planned group by group. These groups are determined by the vehicle size and order size. The steps of the algorithm are as follows: (1) assign the vehicle to groups based on vehicle capacity, (2) assign the orders to groups based on order size, and (3) apply the SIA or the SA per group. This construction method can be used in situations in which specific orders should be given a priority in the scheduling process. The orders that have the highest priority within the group are scheduled first. Then, the second group is scheduled until a predefined number of iterations completes.

- The pickup-and-delivery insertion algorithm (PDIA): When both pickup and delivery orders are to be scheduled, the PDIA should be used. The algorithm consists of the following steps: (1) select the seed order (i.e., from a set of orders with earliest pickup times, select the order with the largest distance between pickup and delivery location as the seed order), (2) select the vehicle with a start location closest to the pickup location that is allowed for the seed, (3) find a cheaper vehicle, (4) add orders to the vehicle until it is full (i.e., for all unplanned orders, determine the best place in the trip for both the pickup and the delivery order), and (5) repeat step 4 until the vehicle is full; then go to step 1.

Improvement Algorithms

Iterative improvement procedures are based on a well-known optimization concept: the neighborhood search. In general, the procedure searches for a better solution, starting from an initial feasible solution. If a better solution is found, the procedure is repeated on the new solution. This process continues until no more improvements are found and a (local) optimum is obtained.

- The optimization algorithms (OptA): After a construction algorithm generates an initial solution, several iterative improvement algorithms, OptA, can be called to improve this solution. These algorithms can be executed successively to find improvements, and the user can specify which algorithms to apply and the order in which to apply them. The user can also specify the maximum number of times each algorithm is allowed to run. Each of these options attempts to reduce the costs of the current planning. Because the application of a specific improvement method may lead to the possibility of improvement by another improvement method, the methods can be called repeatedly.

- The cyclic transfer algorithm (CTA): The CTA makes optimization possible by moving a string of (consecutive) orders between more than two trips. The concept is to iteratively transfer orders among trips in a cyclic manner to improve a given solution.

- The tabu search algorithm (TS): By means of the TS, the current solution is optimized by searching for a better solution in the neighborhood of the current solution. A solution is characterized by the planned trips and the sequence of the orders within the trips. Therefore, the neighborhood of a solution can be defined as a set of solutions with almost identical trips. The elements of this set are called neighbors. From the set of neighbors, the TS selects the best as the new solution, even if this solution is worse than the current solution, unless this solution is on the tabu list (i.e., a list of forbidden solutions). Accepting a solution that is poorer than the current one makes moving away from a local optimum possible, and using a tabu list prevents searching in a cycle. The tabu list stores information about the most recent solutions. The length of the tabu list is the number of iterations for which a solution is forbidden; therefore, after this number has been reached, a solution from the tabu list can be revisited. A solution from the tabu list can also be revisited if specific criteria, the aspiration criteria, are satisfied. For example, when the costs of a solution are lower than the costs of all previously found solutions, this solution will be accepted, although it is on the tabu list.

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Verification Letter

Tjebbe Nabuurs, Manager/Owner, Nabuurs BV, Postbus 183, 5430 AD Cuijk, the Netherlands, writes:

“With this letter, I verify that the material presented in the paper ‘Multidepot Distribution Planning at Logistics Service Provider Nabuurs B.V.’ by Demir, Van Woensel, and De Kok, submitted to the journal *Interfaces, Special Issue on Operations Research in Freight Transportation and Logistics*, consists of a real-life OR application of a transportation planning problem analyzed, designed and implemented at our company, Nabuurs B.V.”

Emrah Demir is an assistant professor in the Operations, Planning, Accounting and Control (OPAC) group of the Department of Industrial Engineering and Innovation Sciences at the Eindhoven University of Technology in the Netherlands. He holds BSc and MSc degrees in industrial engineering from Baskent University of Turkey, and a PhD in management science from the University of Southampton (UK). Dr. Demir's main research areas is positioned within the field of green logistics with respect to externalities of freight transportation.

Tom Van Woensel is a full professor of freight transport and logistics in the OPAC group of the Department of Industrial Engineering and Innovation Sciences at the Eindhoven University of Technology in the Netherlands. He holds an MSc in applied economics and a PhD in operations management from the University of Antwerp, Belgium. He is a board member of the European Supply Chain Forum and an account manager for Bausch & Lomb, Kuehne+Nagel, and Access Business Group with a specialization in distribution logistics, retail operations, and manufacturing systems.

He also heads the Smart Logistics Lab, a joint effort of around 16 people doing research in transport and logistics. His research is mainly focused on freight transport and logistics.

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mathematics from Leiden University, and a PhD in mathematics from the VU University Amsterdam. He is the director of the European Supply Chain Forum and academic director of the TiasNimbas Executive Master of Operations and Supply Chain Excellence and member of the TiasNimbas Academic Council. Professor de Kok has been chair of the subdepartment OPAC since April 2008. His main research areas are supply chain management and concurrent engineering with emphasis on quantitative analysis.