# Exact and heuristic methods for optimization in distributed logistics

Schrotenboer, Albert

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# Chapter 8

## Concluding remarks

We studied optimization problems inspired by recent developments in distributed logistics. Namely, the increasing awareness of sustainability in society and the ongoing struggle of e-commerce companies to become profitable in a landscape of fierce competition. In this context, we focussed on two emerging fields. The first emerging field, which we study in Part I of this thesis, is that of offshore wind maintenance service logistics. The offshore wind industry needs significant cost-savings in the operation and maintenance phase to become competitive with traditional energy suppliers such as coal-based power plants. We develop new methods to determine the short-term maintenance planning, and focused on maintenance planning on a tactical level of decision making as well. The second emerging field, which we study in Part II of this thesis, is that of transportation and logistics related to e-commerce activities. Here, we focused on the design of efficient warehouse order processing methods that incorporate nowaday's key characteristics such as product returns and the many but relatively small customer orders. Besides, we studied the implications of the increasing service requirements (e.g., same-day deliveries) on the design of city distribution delivery networks. Each of the problems that we considered is addressed from an Operations Research perspective. We developed new models and methods that enrich the extant literature and, consequently, are used to analyse the dynamics underlying the optimization problems to be able to provide decision support for practitioners.

In summary, a wide variety of optimization problems inspired by different practical scenarios were considered in this thesis. This wide variety clearly shows the abundance of exciting research that can (and should) be done in this area. Much more research is required to fully understand the dynamics, challenges, and opportunities underlying many recent innovations observed in the applications of distributed logistics. The extent to which current and future businesses can take advantage of these developments will determine if they stay profitable and stay ahead of competitors, and thereby survive in this field of fierce competition. We, therefore, conclude with restating the claim in this thesis' introduction. Indeed, it is an exciting era to work on optimization methods in distributed logistics. It is a field where the continuation of adopting new technology and the development of novel business models is more than ever prevalent.

In the following, we conclude and discuss the main results of this thesis' both parts.

## 8.1 Offshore wind logistics

In Chapters 2-4, we introduced new optimization models that relate to planning maintenance activities at offshore wind farms. We address these problems from an Operations Research perspective focusing on the underlying mathematical problems that relate to vehicle routing and network design. This is in high contrast with most of the literature on offshore wind maintenance service logistics, which predominantly describes new decision support tools and reliability engineering and maintenance-oriented studies. We studied the essence of the underlying mathematical models driving operational and tactical operations. Consequently, we increased the understanding on a fundamental level, which can be incorporated in tomorrow's decision making for real-life offshore wind farms. In the following, we first summarize our main findings and afterward provide suggestions for future research while discussing our work.

### 8.1.1 Conclusions

In Chapter 2, we addressed a single wind-farm, single depot (i.e., port) scenario that is often encountered in practical situations of offshore wind. We formally introduce the Multiperiod Service Planning and Routing Problem (MSPRP), in which one determines an optimal short-term maintenance planning. The major complicating factor is that the maintenance tasks require distinct sets of differently skilled (and scarcely available) technicians as well as spare parts. Both technicians and spare parts need to be transported by a limited fleet of vessels, resulting in a complex optimization problem. With the development of resource-exceeding route inequalities, we were able to develop an efficient branch-and-price-and-cut algorithm for solving this problem to optimality. The inequalities developed can be applied to any routing problem that involves a scarce set of resources. Examples include forestry applications in which heavy equipment needs to be distributed daily to distinct worksites. For the MSPRP, the inequalities were found to be very effective by reducing root node optimality gaps by on average 63.20%. Another troubling difficulty, in an algorithmic-technical sense, is the inclusion of fixed costs for technicians going offshore. The fixed costs cause a violation of some fundamental assumptions that are crucial for efficient column generation techniques. We overcame this problem by developing a tailored algorithm for pricing new columns. In the end, the branch-and-price-and-cut algorithm developed can solve instances of up to 92 nodes and 21 periods to optimality. Besides, we observe that the structure of the optimal solutions depends heavily on the trade-off between travel costs, maintenance costs, and technician costs. Reusing technicians for multiple maintenance tasks results in a higher mean time to maintenance. On the other hand, using technicians simultaneously leads to higher (fixed) technician costs but a lower mean time to maintenance. Depending on the actual parameters, differently structured routes and associated maintenance plannings will be developed.

In Chapter 3, we extended the setting studied in Chapter 2 to multiple wind farms and multiple depots (i.e., ports). Nowadays, it is observed that a single maintenance service provider becomes responsible for the maintenance of multiple wind farms. Here, operations are typically organized from distinct operating and maintenance bases (i.e., ports or depots). In particular, we were interested in the impact of coordinating activities as a whole instead of organizing maintenance operations in isolation at each operating and maintenance base. In other words, we studied the cost-savings potential of collectively using the technicians. We did so by introducing the Technician Allocation and Routing Problem (TARP), and two variants that allow for a certain extent of technician sharing. Whereas in the TARP technicians are not shared, the first variant allows determining the technician allocation once before the operations begin. In the second variant, we allowed for a daily reassignment of technicians among operating and maintenance bases. The TARP is thought to be intractable for exact solution methods. Therefore, we proposed an Adaptive Large Neighborhood Search that has been shown to find high-quality, and often optimal solutions on a set of existing benchmark instances in the literature. Using the ALNS, we show that the daily reassignment of the scarcely available technicians reduces, on average, costs by around 7%. Besides, the mean time to maintenance is reduced, while fewer vessel trips are needed. The ALNS is an attractive alternative to existing exact solution methods for multiple wind farms with multiple operating bases as the computation times are rather short. Such a fast solution method is especially helpful for practitioners that would like to use such optimization methods on a dynamic basis.

In Chapter 4, we take a tactical point-of-view to the planning of maintenance activities at offshore wind farms. In this setting, we formally introduced the Stochastic Maintenance Fleet Transportation Problem for Offshore wind farms (SMFTPO). In this problem, we aim to find a minimizing assignment of maintenance tasks to vessels while controlling for uncertain maintenance tasks and weather conditions. We modeled the SMFTPO as a two-stage stochastic mixed integer programming problem, and solve it using a Sample Average Approximation algorithm. In the first stage, we assign vessels (that are already owned or chartered) to ports. In the second stage, after observing uncertain maintenance tasks and weather conditions, we assign maintenance tasks to the vessels. Different from the existing literature, we take the viewpoint of a single maintenance service provider that does not own the wind farm. Hence, the service provider does not bear the risk of downtime costs. The maintenance provider's only needs to adhere to minimum service requirements specifying contractually binding performance criteria. We consider three of such requirements, namely, to schedule all maintenance tasks, to leave a fraction unscheduled, and to incentivize performing maintenance rather quickly. These stylized settings suffice in providing realistic cost-estimations for performing maintenance under different contractual incentives.

Moreover, in Chapter 4 as well, we provide a review of common assumptions on an operational level for tactical decision making in offshore wind. These assumptions directly impact the second-stage decision of the SMFTPO, namely, how maintenance tasks are assigned to maintenance activities. We extensively compare the impact of different assumptions on the resulting estimation of the operational costs by solving reformulated second-stage problems. We find that for single wind farm scenarios, there is no need to preprocess maintenance tasks in so-called maintenance bundles (i.e., complete daily tasks). Furthermore, allowing for 2% of maintenance tasks unscheduled leads to cost reductions around 8%, and to give an incentive to perform maintenance rather quickly leads to cost increases around 10%. Consequently, we solve the two-stage stochastic programming models by means of sample average approximation. Incorporating the stochastic nature of maintenance tasks is shown to be crucial for these type of tactical decisions since the value of the stochastic solution is large. Besides, we estimate the expected value of perfect information around 10%.

### 8.1.2 Discussion and future research

In Chapters 2 and 3, we obtained a thorough mathematical and computational understanding of the impact of the scarce availability of technicians with different skills. In both the MSPRP (Chapter 2) and the TARP (Chapter 3), deterministic knowledge on future weather conditions is assumed to be available. This is true for many scenarios; for instance, during the summer months in which weather conditions are reasonably predictable. However, in the months preceding and after the winter, this is less likely. Hence, it is valuable to extend the line of research for determining short-term maintenance plannings by considering stochastic (or at least predictions of) weather conditions. A two-stage stochastic optimization model on a rolling horizon basis is then a suitable approach.

Another limiting assumption in Chapters 2-4 is the assumed availability of spare parts. In practice, spare parts might not be available, and the corresponding maintenance tasks can therefore not always be scheduled in each period. Hence, further integration with advanced inventory control concepts is deemed required to increase the embracement of the models developed in this thesis by practitioners.

In Chapters 2 and 3, we observed that the availability and costs of technicians have a high impact on the structure of the optimal solutions. For practitioners, it is, therefore, essential to hire and assign the right technicians to the proper operating and maintenance basis. In line with existing research, we assumed that vessels work independently and, consequently, technicians cannot be transferred between vessels during the day. However, additional efficiency will be obtained if coordinated routing is employed. Then, technicians can be transferred between vessels either directly or via turbines, which is nowadays allowed due to advanced medical training of the technicians. Such advanced control concepts touch upon the notion of transshipments or transfers in pickup-and-delivery problems, which is a very complicating characteristic for routing problems. Extending our research in this direction then offers opportunities from a methodological point of view, as well as it enhances the practicality of the models studied.

We argued in Chapter 4 that single, large maintenance providers are becoming responsible for maintaining multiple wind farms, and do not bear the risk of the turbines' downtime. The cost-structures underlying the MSPRP and TARP in Chapter 2 and 3 are flexible concerning whether or not these downtime costs are incorporated. Nevertheless, the problems studied in this thesis are considered in isolation of the energy market. A further extension of our research will be the consideration of an offshore wind farm that is required to predict its future energy production. This incorporation puts new restrictions on the extent to which maintenance activities can take place. Also, sophisticated decision-making might result in a more reliable prediction of future energy production, possibly leading to an on-average higher output of the offshore wind farm.

In Chapter 4, we showed that assumptions on an operational level are required for solving tactical (and strategical) maintenance planning problems. There, we give an exact characterization of the operational activities for varying assumptions. However, it might be valuable to develop approximation algorithms for the operational problems studied in Chapters 2 and 3. Then, such approximations can be used in tactical (or strategic) models as considered in Chapter 3. This will enhance the solvability of large and long-term strategic models at the expense of not modeling the operational activities exactly. Such approximation algorithms open the door for fewer restrictions on the operational problem, and further research should show whether such an approach will result in reliable cost-predictions.

Finally, as the offshore wind market will get more mature, there might develop a need for dynamic decision making. In Chapter 4, we showed there is still an estimated gap of 10% between the proposed two-stage stochastic programming solutions and the expected value of perfect information. Although the latter is not achievable in practice, it is promising to enhance the level of dynamism in our models (and solution approaches) to come closer to the perfect information situation. Hence, there is a need to develop optimization models based on stochastic (approximate) dynamic programming. Another dynamic aspect of offshore wind farms is the abundance of data available which describes the condition of (spare parts of) a turbine. This, typically real-time information, might be incorporated in such dynamic models as well.

Concluding, our work on offshore wind logistics is part of a research stream that is a natural starting point for many more exciting research topics. The main objectives should then be to integrate short-term maintenance planning problems with other domains of importance for offshore wind logistics. Examples include condition monitoring, spare parts inventory management, the dynamics of energy markets, and a computationally tractable integration with large-scale strategic planning problems.

## 8.2 E-commerce logistics

In Chapters 5-7, we introduced new optimization models inspired on emerging topics related to the rise of e-commerce companies. The primary motivating development for the design of these models is the increasing number of customer orders that are increasingly complicated to process (e.g., same-day delivery). On the one hand, new paradigms for customer order processing in (city) distribution centers are required to deal with a large number of typically small-sized customer orders and the significant stream of product returns. On the other hand, this necessitates the design of city distribution networks in which temporal (i.e., time) aspects of the distribution are managed precisely to enable efficient consolidation of parcels.

### 8.2.1 Conclusions

In Chapter 5, we studied how to include the restocking of returned products in regular order picker routes in picker-to-parts warehouses. In this Traveling Salesman Problem with Pickup and Deliveries (TSPPD), one designs a route in a warehouse so that all deliveries (that are initially on the depot) are brought back to their storage locations while a set of new products is picked. We develop a Hybrid Genetic Algorithm to solve the TSPPD. The genetic algorithm provides high-quality and often optimal solutions for small-scale instances, as is shown by a comparison against solving a MIP formulation for the TSPPD with a commercial solver. Experiments on a carefully constructed case did show that integration of product returns can lead to 23.48% less distance traveled, compared to processing the product returns and new orders separately. Besides, we also studied the effect of order picker blocking by considering multiple order pickers that travel simultaneously through the warehouse. For a given start-time, we count the number of times the order pickers would cross in the warehouse while they traverse their routes. To find high-quality solutions that incorporate this penalty, we proposed another Hybrid Genetic Algorithm. We found that small alterations to the order picker routes (only leading to marginal increases in travel distance) can almost eliminate picker blocking (or any interaction). In other words, multiple near-optimal solutions are significantly different from each other. Therefore, secondary objectives can be successfully incorporated relatively easily.

In Chapter 6, we extend the concept of integrating product returns in regular order picking processes (as studied in Chapter 5) by considering a setting that goes beyond order picker routing only. In the Generalized Joint Order Batching, Assignment, Sequencing, and Routing Problem (G-JOBASRP), we consider next to order picker routing, the design of order picker batches, the assignment of batches to order pickers, and the sequencing of those batches for each order picker. We aim to minimize the sum of routing costs (inside the warehouse), tardiness costs (i.e., violation of customer deadlines), and so-called split-up costs. These latter costs are stylized costs that resemble additional handling operations (outside our modeled operations) resulting from splitting up customer orders amongst multiple order-picking batches. We develop a parallel Adaptive Large Neighbourhood Search which significantly outperforms commonly-used, practical heuristics for instances up to 8038 to be processed order lines.

We show that integrating product returns in the G-JOBASRP is particularly useful for warehouses not working at their full capacity, which is throughout most of the year. Besides, we observe that the total costs can be reduced by up to 45% if customer orders can freely be split-up, compared to if customer orders cannot be split-up. For small values of the stylized split-up cost, we find that significant cost-savings can still be obtained. It is observed that increasing split-up costs predominantly leads to an increase in travel costs instead of a major rise in incurred split-up costs. Apparently, it is cost-efficient to avoid customer split-ups at the costs of increasing travel costs. This last observation also strengthens the claim made in Chapter 6 that the TSPPD has relatively many near-optimal but structurally different solutions. Also in the G-JOBASRP, routes with slightly higher travel costs are chosen instead of simply incurring split-up costs. The structure of these routes is significantly different from the case without split-up costs.

In Chapter 7, we took a more strategic view of e-commerce operations. Instead of focussing on warehouse operations, we studied the design of robust city logistics networks. Such networks are designed so that day-to-day operations subject to temporal (i.e., time) uncertainties can be organized efficiently. We formalized this in the two-stage network design problem with temporal characteristics (RND), which represents the design of a network to enable commodity streams between (city) distribution centers. In the RND, we make decisions in two-stages. In the first stage, we select vehicle paths through the given network without determining actual departure or arrival times. Then, we observe the stochastic temporal characteristics, including the earliest possible pickup time and the latest possible delivery time of the commodities to be transported in the network. In the second stage, we decide upon the departure and arrival times of the vehicle paths chosen in the first stage. By taking a robust approach, we ensure that the sum of first-stage vehicle path costs and worst-case second stage costs are minimized. This is, by the best of our knowledge, the first study that takes such a robust optimization approach in the context of city distribution networks with temporal characteristics. This is relatively surprising, as network design with temporal characteristics is pre-eminent an application in which small disturbances have a high impact on the validity of the solutions proposed. We provided a general two-stage robust integer formulation, its associated large-scale scenario-based MIP formulation, and a tractable counterpart of the static variant of the problem considered. A detailed analysis showed the benefit of using the concept we propose.

### 8.2.2 Discussion and future research

From Chapter 5 and 6, we obtained a good understanding of the impact of incorporating product returns in regular order picking processes. Both the TSPPD and the G-JOBASRP are, however, based upon a perfect knowledge of customer demand. With the increase of same-day delivery or even ‘within two hours delivery’, more dynamic optimization approaches become relevant. Real-time routing of order pickers, or the real-time routing of robots in mechanized warehouse concepts, might, therefore, be of particular interest for future researchers. Approximate dynamic programming approaches will become usefull to solve such problems.

Moreover, both the TSPPD and the G-JOBASRP assumed a random storage location assignment of products to warehouses. In practice, one typically exploits storage assignment strategies based upon the frequency of products being ordered and the correlation between product orders. The integration of storage assignment into the G-JOBASRP is, therefore, the next step into solving integrated warehouse order processing problems. Besides this integration inside the warehouse, other integrations outside the warehouse are prevalent as well. Consider, for instance, the scheduling of trucks to pick up and deliver shipments to and from the warehouse. However, such integrated problems will become intractable to solve, even with metaheuristic techniques. It is, therefore, that approximations of operational performance inside the warehouse might be useful for such integrated settings. To the best of the author's knowledge, no such research has yet been done despite its practical relevancy.

Besides, whereas we considered the impact of order picker interaction (e.g., blocking in narrow aisles) in the TSPPD (Chapter 5), we did not consider this in the G-JOBASRP. Including this aspect might reduce the practicality of splitting customer orders amongst multiple batches, as order picker routes are likely to consists of only a few visited aisles, leading to more interaction and delays due to order pickers crossing. Furthermore, precise modeling of operations outside the warehouse might shed more light on the impact of splitting up customer orders. This will quantify the effect of splitting up customer orders, and making this visible is crucial for the embracement by practitioners.

Furthermore, there is the need for more rigid exact solution methods based upon column generation or Lagrangian relaxation, especially for the large-scale instances considered in the G-JOBASRP and encountered in practice nowadays. If such approaches were developed, it would enable the assessment of the quality of the proposed solutions for such large-scale instances. Only then it will be known if more research should be spent on the development of metaheuristic (or other heuristic) approaches for solving (variations of) the G-JOBASRP.

Many opportunities for future research arise in the context of network design and robust optimization. First, and foremost, the presented algorithm in Chapter 5 is not yet able to provide optimal solutions to large-scale RNDP instances. A column-generation based method is required on top of efficiently solving the second-stage subproblem. The latter involves benders decomposition methods, and consequently, Benders decomposition is included as part of the column-generation procedure. However, this choice is somewhat arbitrary as one could also provide a Benders decomposition method on top of column-generation subprocedures. Future research will determine which structure is more computationally efficient and if there are possibilities to enhance one of the layers with information obtained from the other layer by, for instance, developing valid inequalities. Another avenue for future research is the development of more dynamic methods. Opportunities range from multi-stage robust optimization problems to complete dynamic settings solved with approximate dynamic programming techniques.