Digital Comprehensive Summaries of Uppsala Dissertations
from the Faculty of Science and Technology 2598

Simulation-based multi-objective optimization of wood supply chains

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ACTA UNIVERSITATIS
UPSALIENSIS
2025

ISSN 1651-6214
ISBN 978-91-513-2617-7
urn:nbn:se:uu:diva-568502

UPPSALA
UNIVERSITET

Dissertation presented at Uppsala University to be publicly examined in Häggsalen, Lägerhyddsvägen 1, Ångström Laboratory, Uppsala, Friday, 21 November 2025 at 13:00 for the degree of Doctor of Philosophy. The examination will be conducted in English. Faculty examiner: Professor Mauricio Acuna (Natural Resources Institute Finland).

Abstract
Westlund, K. 2025. Simulation-based multi-objective optimization of wood supply chains. *Digital Comprehensive Summaries of Uppsala Dissertations from the Faculty of Science and Technology* 2598. 79 pp. Uppsala: Acta Universitatis Upsaliensis. ISBN 978-91-513-2617-7.

From a customer's perspective, the wood supply from forest to end users should be timely, of the right quality, and in the right quantities, regardless of supply disturbances. The term delivery performance summarizes these simultaneously and equally important targets for wood supply. Harvesting determines when wood becomes available for transportation, and both harvesting and delivery must align with the customer's monthly demand. Having operative long-term harvest scheduling is the key to fulfilling these multiple delivery targets. At the same time, uncertainties such as weather conditions and product outcomes significantly affect whether deliveries can be made according to schedule. Even with an accurate harvest scheduling, weather-related road accessibility remains a critical success factor for achieving delivery performance. Ideally, the harvest scheduling should offer multiple scheduling options with the best possible performance across as many delivery performance objectives as possible, and be robust to uncertainties.

This research proposes a methodology for harvest scheduling using a simulation-based multi-objective optimization framework. The methodology combines meta-heuristic multi-objective optimization with discrete-event simulation to evaluate delivery performance across multiple objectives. Discrete-event simulation models the wood supply chain, allowing the integration of weather-dependent uncertainties in road accessibility. The framework is tailored to the harvest scheduling problem and is evaluated using different objective functions that represent delivery performance targets. To improve the robustness of the scheduling, various strategies are implemented to handle variability in road accessibility. An architectural design for short-term operational planning is proposed, integrating digital twins and artificial intelligence into the framework to manage real-time uncertainties as part of recently initiated research. The main contribution of this work is a flexible methodology within the simulation-based multi-objective framework that supports varied objectives and solution algorithms. This approach enables simultaneous improvement of multiple delivery performance objectives in the harvest scheduling while addressing uncertainty.

Keywords: Simulation-based optimization, multi-objective optimization, wood supply chains, discrete-event simulation, harvest scheduling, road accessibility

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ISSN 1651-6214
ISBN 978-91-513-2617-7
URN urn:nbn:se:uu:diva-568502 (http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-568502)

To my beloved family — Fredrik, Charlie, and Antonia.

List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I Westlund, K., Engberg Sundström, L. & Eliasson, L. (2024). An optimization and discrete event simulation framework for evaluating delivery performance in Swedish wood supply chains under stochastic weather variations. *International Journal of Forest Engineering*, *35*(2), 326–337. https://doi.org/10.1080/14942119.2024.2313417

II Westlund, K., Ng, A. H. C. & Nourmohammadi, A. (2025). Simulation-based multi-objective optimization to support delivery performance decisions in harvest scheduling and transport. *International Journal of Forest Engineering*. Accepted and published online: https://doi.org/10.1080/14942119.2025.2533083

III Westlund, K. & Ng, A. H. C. (2024). Analyzing Delivery Performance and Robustness of Wood Supply Chains Using Simulation-Based Multi-Objective Optimization. *Proceedings of the 2024 Winter Simulation Conference (WSC), Orlando, FL, USA*, pp. 1587–1598. https://doi.org/10.1109/WSC63780.2024.10838762

IV Westlund, K. & Ng, A. H. C. (2024). Decision-Making in Wood Supply Chain Operations Using Simulation-Based Many-Objective Optimization for Enhancing Delivery Performance and Robustness. *Submitted to the special issue 'IT in Production and Logistics' of the journal Computers*.

V Westlund, K., Engberg Sundström, L., Shavazipour, B. & Ng, A. H. C. (2025). A robust approach for handling deeply uncertain weather-related landing accessibility in harvest scheduling. *Submitted to the Canadian Journal of Forest Research*.

VI Westlund, K. & Ng, A. H. C. (2025). AI-Driven Digital Twin Architecture for Forestry Logistics Planning. *Proceedings of the ASIM-SPL2025 (Simulation in Produktion und Logistik) Conference, 24-26 September, Dresden, Germany*, pp. 26-1–26-10. https://doi.org/10.25368/2025.233

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Abbreviations

AI	Artificial intelligence
DES	Discrete-event simulation
DSR	Design science research
DT	Digital twin
MOO	Multi- and many-objective optimization
RL	Reinforcement learning
SMO	Simulation-based multi-objective optimization
WSC	Wood supply chain

Acknowledgements

This dissertation is the last and summarizing step of a learning path. PhD studies, after all, are an education in how to conduct research and become a researcher, which entails learning various types of skills. Along this journey, there have been challenges and uncertainties, among others, the Covid-19 pandemic and several sudden family situations. Nonetheless, I have reached this final step, for which I am grateful - it marks the culmination of and reward for my efforts.

I gratefully acknowledge the financial support provided by Stiftelsen för Strategisk Forskning, through grant agreement [FID17-0043], that made this dissertation possible.

I would like to express my gratitude to all who supported and guided me during this work. Particularly my main supervisor, Professor Amos H.C. Ng, for his invaluable guidance, support, and encouragement in all and every situation. I am also grateful to my co-supervisors. Dr. Lars Eliasson for his meticulous proofreading, comments and coordination of the project, Dr. Lovisa Engberg Sundström for encouragement and forward-looking technical discussions, Dr. Matías Urenda Moris and Dr. Daniel Noreland for keeping the "helicopter perspective" of what aspects are more important than others. My appreciation also goes to the supportive colleagues at Skogforsk.

I would like to thank my friends for their constant encouragement and patience in waiting for me to socialize.

Finally, my sincere gratitude to my family who supported me in good and in worse times, every day, on holidays or otherwise, and with endless understanding. Thank you for everything.

1. Introduction

This chapter introduces the research by presenting the background and the problem description that motivated the study. It articulates the research aim, formulates the research questions, and outlines the research approach employed. The chapter concludes with an overview of the thesis structure.

1.1 Background

Forest wood products are critical in the transition to a bio-based economy, where valuable products must be delivered on time and with minimal risk of quality degradation. The wood supply chain (WSC) encompasses all processes, from harvesting to delivery to the mill (customer), including transportation. Maximizing the utilization of harvested raw material is critical for achieving resource efficiency, optimizing yield, and ensuring that the material is used to its fullest once harvested. This implies that accurate deliveries in response to customers' diverse requirements must be optimized to the greatest degree possible, while simultaneously maximizing the utilization of wood resources from both economic and sustainability perspectives. Wood procurement is subject to stochastic variations and requires robust planning models to ensure the supply of raw materials. This thesis aims to develop a methodology to improve delivery performance across multiple targets within the WSC while addressing key sources of variability. To enhance the robustness of delivery performance, methods and strategies must address stochastic variations, such as the accessibility of roads and landings, within the scheduling process.

Approximately 87.6 million cubic meters of wood are harvested annually in Sweden across about 530,000 hectares, with the average harvest site measuring about 3.6 hectares (Skogsstyrelsen, 2025). Two-thirds of the harvested volume comes from around 60,000 final felling operations (Asmoarp et al., 2020), and most of the remainder comes from at least as many thinning operations. Harvested and forwarded wood products are transported from landings to different mills, where they are transformed into a range of bio-based products (Kungliga Skogs- och Lantbruksakademien KSLA, 2014). The Swedish forest industry is the fifth-largest exporter of pulp, paper, and sawn wood products globally, with 80 percent of wood products being exported (Skogsindustrierna, 2020).

The Swedish wood and biomass used in sawmills, pulp mills, and the heat and power industries are sourced from private forest owners, company-owned

forests, state forests, municipal forests, and other public owners. A harvesting operation typically produces between three and ten products destined for different customers. In strategic harvest planning, production, transportation, and delivery are allocated to the shortest path to customers based on estimated product volumes. Strategic planning is conducted in advance to maximize landowner revenue by minimizing transport costs to customers. Product volumes are estimated for each site to support planning, evaluate how well annual customer demand can be met, and schedule the operational supply chain to ensure even delivery flows to customers. Multiple stakeholders, including service providers such as harvesting contractors and transportation companies, play a role in the WSC ensuring the delivery of products to customers, where real-world factors such as weather affect the deliveries.

Delivery performance from the customer's perspective includes more than one goal or objective. A common focus is on timely deliveries of wood products of a specific quality. Monthly quotas at the mills should be filled to ensure minimal backlogs and a smooth and even flow. Customers do not want erratic flows, but rather flows that vary as little as possible according to monthly and annual demand. The requirements to fulfill a product specification are based on the customer's demand and commonly agreed-upon business rules. Quality definitions are typical requirements, specified for different products (Biometria, 2025). Most of the lead time from the forest to the customers is due to storage time at roadside landings. To reduce the risk of quality degradation, the focus is on minimizing long storage times, where scheduling aims to reduce storage time at landings to mitigate the risk of quality devaluation (Kogler & Rauch, 2023; Palander et al., 2024).

All transportation from harvesting sites is carried out exclusively by trucks, either directly to mills or terminals for storage and transshipment to a boat or to trains for long-distance transport, i.e., distances exceeding approximately 100 km. The logistics chain must be agile and adaptable to new situations, such as weather-related impacts on landing accessibility and unexpected variations in products. To ensure timely deliveries, wood supply must be scheduled to meet customer requirements, with the supply chain process beginning in the forest with harvesting operations. The schedule must account for all stakeholders, the complexity of interactions between service providers (e.g., harvesting teams, transportation, etc.), and how these processes work together to deliver the required quantity and quality of wood on time and at a preferred high production rate (throughput).

Efficient supply chain management is expected to handle variations effectively as they occur while maintaining the delivery schedule. Uncertainties in product outcomes from harvesting make scheduling precision difficult, despite the pre-estimation of products. It is crucial to fulfill deliveries for the many wood products, both when roads are accessible and when accessibility is limited, e.g., during a thawing or rainy period. Additionally, social demands, such as minimizing impact and reducing the risk of road damage from transports,

must be considered. However, customers' requirements must be met regardless of the weather. Weather significantly affects landing accessibility, which, in turn, has a major impact on wood supply logistics and delivery performance. A changing climate increases the risks of reduced landing accessibility, which can lead to value loss or road disruptions. Therefore, access to landings must be actively considered and integrated into scheduling. Accessible areas are often reserved year-round as a rule for use as needed, to ensure deliveries and minimize environmental impacts. Interim storage at terminals is another method used to secure wood deliveries, for example, during the thawing period, but it entails increased costs. Because forest roads with year-round accessibility are limited, it will be necessary not only to include accessibility as a factor in operations scheduling, but also to evaluate schedules for robustness when road accessibility predictions deviate from those anticipated.

Climate change poses growing challenges for Swedish WSCs (Lehtonen et al., 2019). Wood risks being trapped in landings, resulting in increased storage time and a higher risk of quality degradation. This corresponds to the risk of damaged roads and the costs of road restoration. Today, truck transport is sometimes forced to use roads with low bearing capacity in thawing periods. An increase in average monthly precipitation and a reduction in days with frozen ground conditions are expected in the near future (Daniel et al., 2018; Kellomäki et al., 2010; Lehtonen et al., 2019), entailing growing challenges for wood transportation on forest roads. The share of operations conducted under less favorable circumstances is thus increasing. At the same time, the pressure on just-in-time deliveries is increasing for both consistent wood quality and for wood cut to length using sawmill specifications based on their current orders. The scheduling should account for both multiple delivery objectives and approaches to managing uncertainties facing forest management. This critically impacts the accuracy and effectiveness of scheduling, creating a need for more flexible, robust, and adaptable production scheduling that considers changing conditions (Acuna et al., 2019; Malladi & Sowlati, 2017).

1.2 Problem description

Customers expect wood deliveries to arrive on time and meet the requirements for product volume and quality. Delivery performance metrics can vary depending on whether it is from the customer's or supplier's perspective (Forslund & Jonsson, 2007). However, to achieve delivery performance focused on customers' values, the objectives must reflect customers' priorities. Measures related to the quality and on-time delivery of product volumes are prioritized, which can be reflected in delivery penalties or rewards. The deliveries are measured in, e.g., monthly delivery quotas for the forest companies and are determined based on product quantity for a certain quality. Delivery according to quota can be rewarded, and under-delivery can be penalized. This, in turn,

implies the multiple delivery performance objectives to be achieved regardless of variations in the supply chain.

All stakeholders in the supply chain should strive to maintain low backlogs, nondelayed deliveries, and short lead times, which is the time it takes from harvest to delivery (Hopp, 2011, Ch.2; Pound et al., 2014, Ch.3), to reduce the risk of quality degradation. From harvesting to delivery to the industry, the longest lead time occurs during storage in landings. Quality depends on lead time, with shorter lead times being preferable. Long storage times can alter quality, as observed in studies on both energy wood, where the moisture content decreases (Erber et al., 2014; Eriksson et al., 2017), and round wood, where the risk of degradation increases (Rauch et al., 2022). For energy wood, this means a quality improvement, but for sawlogs, quality is at risk (Palander et al., 2024). Additionally, production and transport throughput should be as efficient as possible (Pound et al., 2014, Ch. 3), delivering the highest possible volume (m^3) per unit of time. For each supply chain, the delivery performance objectives must be determined based on specific goals. Saw and pulp mills are often large, where even input is required to keep mill production running at the same pace, regardless of external factors. In strategic planning, the wood is allocated from a harvesting site to a designated industry prior to the operational harvest scheduling. For strategic planning, catchment areas are determined for the industries (Forsberg et al., 2013). These areas, or regions, define which harvest sites should be allocated to which industries, to fulfill demand by matching estimates of product outcomes while minimizing overall transport distances. Delivering wood at an even pace requires scheduling the supply, where the starting point for delivering a cubic meter of wood to the customer is harvesting. Key factors include when harvesting starts, the lead time in the supply chain to delivery, the delivery time, and how aggregated volumes fulfill a customer's demand.

The optimized annual plan holds in a static world. But when variations in, e.g., production volumes or road accessibility become part of the picture, new prerequisites emerge. Harvest scheduling should account for variations, enabling provision of more robust solutions to obtain delivery performance. Moreover, when variations occur, there may be competing goals. Timely deliveries are supported by larger volumes on landings, making it easier to aggregate sufficient quantities to fulfill customer quotas in time. However, storing large wood volumes on landings poses a quality risk, especially in warm weather or when storage times increase. Occasionally, weather conditions make landings inaccessible, as roads are only constructed for transport under specific weather conditions. Inaccessible landings further increase the risk of prolonged storage times. These objectives, lead time and on-time delivery, are concurrent, meaning prioritizing one affects the other. Additionally, other objectives, such as throughput, must be optimized simultaneously. Supportive information, or ideally, a decision support system, can help decision-makers understand the actual

trade-offs between multiple delivery goals while accounting for variations in road accessibility.

Achieving multiple goals or objectives in a predictable environment is a complex problem that involves numerous supply chain processes, where uncertainties add further pressure. Road accessibility determines whether landings are accessible for truck transport, but accessibility can vary depending on weather conditions. Although harvest schedules are based on road classes (Biometria, 2021) and existing knowledge of seasonal variations, weather conditions can cause unexpected changes in road accessibility.

In addition, the impact of weather on road accessibility is substantial. In the past, seasonality has been recognized through experience, allowing weather, season, and their impact on road accessibility to be partially accounted for. However, it is not entirely possible to make a plan for this. In the coming years, increased variations are expected due to, e.g., earlier spring periods (Barnett et al., 2005) and a general reduced bearing capacity for both harvest sites and forest roads (Gregow et al., 2011; Kellomäki et al., 2010; Lehtonen et al., 2019). A reduction in accessibility to landings will have consequences for lead time and backlogs, specifically affecting delivery performance. This justifies the research on the effects of road accessibility on wood supply, including road accessibility variations in the harvest scheduling problem. It also emphasizes planning the WSC to make more informed decisions in scheduling, targeting multiple delivery performance goals that should also be robust to variations.

1.3 Aim

This dissertation aims to explore and develop a methodology for simulation-based multi-objective optimization (SMO), focusing on its practical applications in supporting decision-making in WSC management, while accounting for multiple conflicting objectives when faced with relevant uncertainties.

1.4 Research questions

The overarching research goal is to develop and apply SMO for wood supply scheduling as a methodology, incorporating the customer's multiple, conflicting optimization objectives. This methodology emphasizes robustness by addressing variations in deliveries and road accessibility, ensuring that schedules account for uncertainties in wood flow disruptions. Four interconnected research questions (RQs) emerged from this problem description and the overall study:

RQ1. Can SMO effectively handle the stochastic nature of the forestry supply chain, providing more robust system configuration solutions and more accurate cycle-time evaluations than classical optimization approaches?

RQ2. How should deviations between planned, mathematically optimized deliveries and actual (stochastically affected) deliveries be handled? When is it necessary to re-plan (re-optimize) the deliveries or accurate to continue management based on simpler decision rules?

RQ3. Regarding the influence of input data quality on optimization results: How do inaccurate data influence system planning?

RQ4. How can real-time updates of input data improve planning activities in a WSC?

RQ1 explores how SMO can be applied to the multiple delivery performance targets of the supply chain. Simulation is widely used in WSC research as a means of imitating the supply chain to generate predictive scenarios. Single-objective optimization (classical optimization), which typically focuses on a monetary unit, differs significantly from a multi-objective optimization approach. Multi-objective problems can be approached in various ways. A commonly used method is scalarization, where objectives are weighted and often converted into a standard monetary unit, such as cost, to make them suitable for single-objective methods. In contrast, the focus here is on exploring methodologies that utilize multi-objective optimization to simultaneously compare objectives representing distinct delivery targets, which may also be expressed in different units. This approach requires making trade-off decisions regarding how to prioritize the objectives — an aspect that differs from single-objective optimization and involves the participation of a decision-maker. The combination of simulation and multi-objective optimization enables both prediction of outcomes in a complex supply chain and optimization of multiple concurrent objectives.

RQ1 and RQ2 address the delivery variations, mainly caused by (restricted) road accessibility, which has a great impact on deliveries. To answer this, variations in road accessibility must be evaluated, as well as the methodology and design of the models adopted to handle these variations. RQ1 and RQ2 address the robustness aspect of the overall research goal, aiming to enhance the robustness of operational wood supply scheduling by handling variations in accessibility to landings due to weather conditions. Robustness is approached by robust design, to identify and reduce the effects of variations in the deliveries.

RQs 3 and 4 relate to how the quality and precision of input data affect the scheduling of the WSC and how real-time data can improve scheduling. Absence or poor quality of input data may also result in an inaccurate reflection of real-world conditions and can drastically alter the conditions of an already

established supply schedule. The issue in RQ3 addresses both existing input data and how inaccurate or lacking relevant data can be managed within the optimization process. Furthermore, it connects to RQ2 regarding how the modeling can be more robust to variations related to insufficient input data.

RQ4 addresses how real-time data can further improve scheduling. This question takes RQ3 one step further in describing available and timely input data that can reflect the actual situation of the supply chain in real-time and how these data, if available, can be utilized.

1.5 Limitations

The research presented in this thesis focuses on developing an SMO methodology for wood supply scheduling to handle multiple objectives at sites where the products are already designated for specific customers. Some assumptions were made in the context of the work. There could be objectives other than those used in this work. However, the objectives most commonly used for any WSC are related to delivery time and timely, reliable, and consistent deliveries, which are reflected in the objectives used. In the pre-planning phase of harvest scheduling, strategic planning is conducted, where harvest site regions are often allocated to specific industries based on defined catchment areas. This approach aims to meet the demand for estimated annual product volumes while minimizing transport distances to customers. It is particularly relevant for landowners who own mills or have customer delivery contracts. The work presented here is primarily based on this premise. However, in the latter part of the dissertation (Paper VI), a CO_2 objective is suggested in the optimization to minimize transport distances for non-designated problems.

Weather and road accessibility can vary stochastically, with accessibility fluctuating from day to night (Väätäinen et al., 2025). An example is when a road becomes accessible at night after a few hours of lower temperatures, causing it to freeze. However, such short-term variations are not the focus of this project. There are also attempts to overcome low carrying capacity, for example, by using specially equipped trucks or temporarily lowering the tonnage for specific transports. This level of detail is excluded as it is not the focus of this project.

The primary focus of most wood supply planning papers has been on economic values (Malladi & Sowlati, 2017). This is not neglected here, although the focus of this dissertation is on the inclusion of other equally important objectives, which, in turn, are crucial for achieving other monetary values within a well-functioning supply chain. However, other objectives that directly address monetary values can be incorporated into another problem setting. Monetary units or economic values can be addressed, among other objectives, whenever a multi-objective approach is employed. This also applies to sustainability measures, which should be defined and developed in collaboration with domain

experts and industry representatives to capture relevant and essential trade-off aspects.

Although the aim is to demonstrate results that approach the level of a prototype decision support tool, the primary emphasis remains on developing and validating the methodology itself. From the author's perspective, achieving prototype-level results represents an important step toward implementing research outcomes in practical forest applications. However, it is essential to note that the design of a fully functional decision support system is beyond the scope of this work, and this thesis does not claim to present a complete or operational decision support system. Visualizations are discussed and presented as examples of possible ways to implement and use the methodology for decision support.

1.6 Research approach

This section outlines the research approach and strategy employed in the dissertation. For the project, the main reasons for the research are to find new methods for application in solving a WSC scheduling problem and to explore and develop a methodology. Design science research (DSR) is presented and utilized as a research strategy to support answering the research questions.

1.6.1 Design science

A research paradigm outlines the typical common characteristics stated by researchers in a particular research field (Säfsten & Gustavsson, 2019). As described by Säfsten and Gustavsson (2019), a paradigm shares a common understanding in the sense of a shared perception of the context, including theories, research methods, and a knowledge-based approach within the research field. It encompasses the research approach as a regulatory guide for outlining and performing the research (Cecez-Kecmanovic & Kennan, 2018).

Oates (2005, Ch. 2) describes the purpose of the research as a response to one or more of six purposes. Three of the purposes are "to find out what happens," "to solve a problem," and "to predict, plan and control." Together, these purposes describe this dissertation, which aims to develop new methodologies that contribute to better understanding, prediction, planning, and control to improve deliveries in the WSC. This research lies at the intersection of multiple domains: forest science, simulation and optimization, and system design and software development. Ultimately, it incorporates systems, computation, and computer technology to develop a methodology. A methodology is designed to understand the problem within its context and, through experimentation, explore different scenarios to investigate how an input affects an output. All these aspects are encountered in this project and dissertation process of developing

an SMO framework for the WSC. Finally, the purpose is to present a prototype of the methodology as an answer to how to solve a problem.

The traditional and dominant research paradigms are positivism, interpretivism, critical realism, and pragmatism, where the latter two are closest to an abductive research logic (Säfsten & Gustavsson, 2019). In abductive research, the result leads to creating a rule explaining the problem, which is confirmed based on observations (Säfsten & Gustavsson, 2019, p. 50), which is close to the DSR methodology. Freely translated, Säfsten and Gustavsson (2019, p. 36) defines methodology, the study of methods, as the link between the assumptions made about the world and how it can be investigated—an overarching logic for how a study should be conducted. The methodology serves as the framework for selecting research methods. As described by Peffers et al. (2018), traditional research paradigms from the natural and social sciences are focused on descriptive and explanatory research, which differs from prescriptive research, the aim of which is to create an applicable solution to a problem. DSR is often proposed and applied as a scientific research approach for information technology research, where the outcome is usually a system or application. Holmström et al. (2009) describe DSR as a bridge between theoretical academic research and managerial practice, applying research to solve real-world problems for practical applications. The DSR methodology is defined by Johannesson and Perjons (2014) as a combination of different sciences (social, behavioral, and formal) employed to study the development and use of artifacts for problem-solving. An artifact can be anything used to solve the problem, but for simplicity, it can be described as a model, a system, an application, an algorithm, or a framework. The artifact does not solve the problem itself, but rather serves as an aid used to explore it (Wieringa, 2014, Ch. 3). DSR is described as a customized research methodology for designing artifacts to improve something for a stakeholder (Wieringa, 2014, Ch. 3).

Hevner and Chatterjee (2010) describe DSR as:

> Design science research is a research paradigm in which a designer answers questions relevant to human problems by creating innovative artifacts, thereby contributing new knowledge to scientific evidence. The designed artifacts are both useful and fundamental in understanding this problem (Hevner & Chatterjee, 2010, p. 5).

The artifact is the response that allows the researcher to gain knowledge and understanding of the design problem. It interacts with a problem and is designed to capture the problem context, to create a methodology or system that can extend the knowledge to search for solutions to the problem. DSR is an iterative process, Figure 1.1 (Hevner & Chatterjee, 2010, p. 16), where knowledge collection is the foundation for modeling the artifact. Vice versa, the artifact can contribute to increased knowledge of the problem. This is an iterative process.

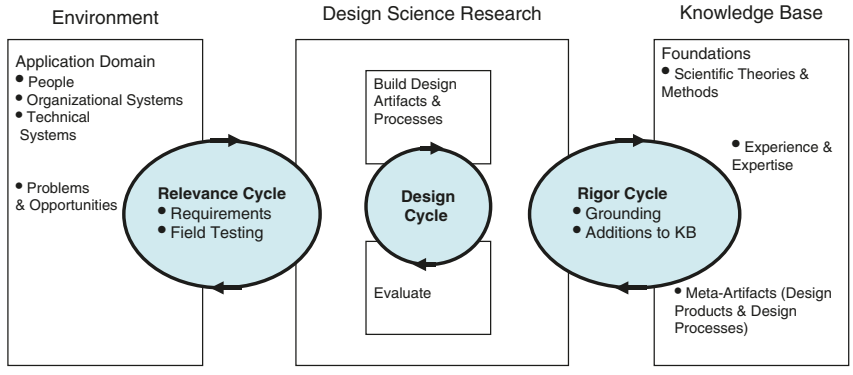


Figure 1.1. DSR cycles, adopted from Hevner and Chatterjee (2010, p. 16).

Decision support is a more concrete example of a typical artifact (March & Smith, 1995), where interactions from different inputs reflect possible decision choices or outputs. The basis for DSR is understanding the context of the problem, including the goals of the supply chain and the decisions that managers face. To design and develop an artifact, it is essential to explore the stakeholders' goals and the environment in which the problem occurs. A systems analysis provides the groundwork for understanding the context of the situation, enabling the solution and design of the artifact. Combining strict objectivity in the search for an answer and the iterative research process and adding new findings from new knowledge are also typical of developing and improving new models or artifacts.

Arnott and Pervan (2014) conclude that the DSR method had an impact and is predominant in decision support systems research. The DSR approach is designed for this type of research. It conforms to the outlined research questions to iteratively develop and improve a methodology that increases awareness of the problem context, implements the knowledge, and refines the artifact. In general, the goal is to explore new theories, describe explanatory variables, their mutual relations, and how they impact the objectives, and seek answers to research questions. Therefore, the DSR approach was employed in this work, designed to develop a framework that supports decision-makers in improving delivery performance when scheduling harvesting operations. This thesis explores methodologies to help managers make decisions with multiple objectives in the WSC using a decision support system based on simulation-based optimization and visualization of results. Decision-making and information collection are daily tasks allowing managers to make informed decisions. However, using SMO to improve delivery performance while considering uncertainties in road accessibility is a new application in wood supply scheduling.

1.6.2 Research process

The practical research work, which develops the simulation-based multi-objective methodology for a WSC application, is described in Figure 1.2 and its connection to the DSR approach, where the design was iteratively developed. The research process is described in more detail in Figure 1.3.

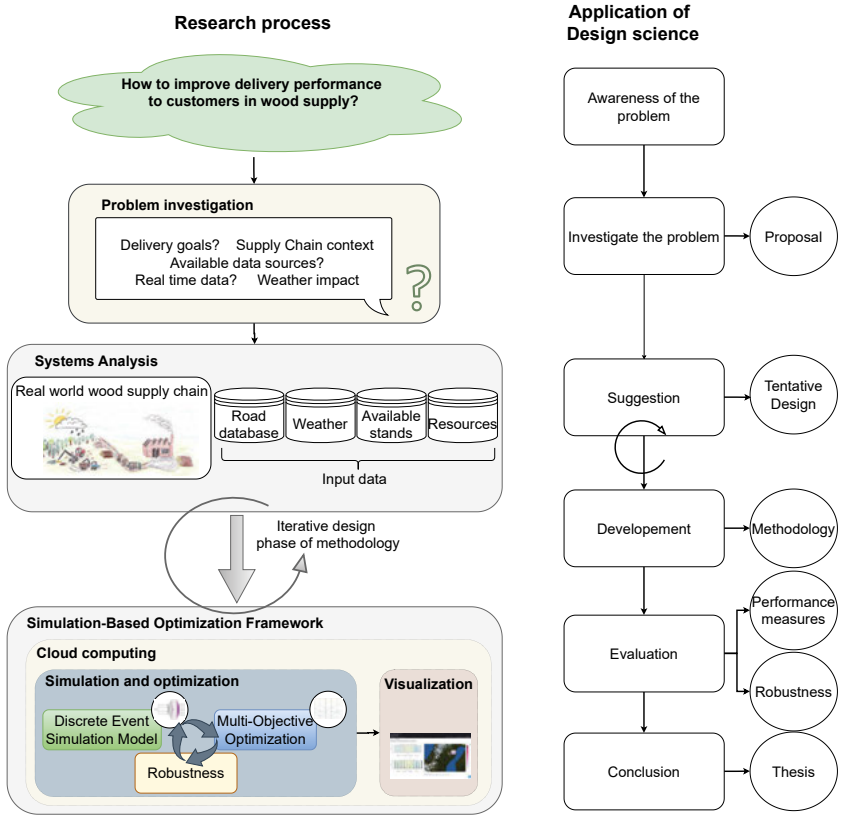


Figure 1.2. Practical research work and linkage to Design science.

The primary identified domains in focus, as defined by the research questions, are the research areas for the project. Each research area contributes to the final methodology. The research areas are the following:

- Discrete-event simulation (DES) of the WSC
- Multi- and many-objective optimization (MOO) methodologies
- Robustness, a robust design that addresses variations in deliveries

1.7 Research outcomes - an overview

As described by Oates (2005, Ch. 2), the purpose of research is to answer a question, with new knowledge being the product, i.e., the research outcome. Per-

spectives of different researchers can increase the insights gained and contribute to the development of new knowledge (Oates, 2005, Ch. 2) and research products. This thesis falls under one of the defined categories of research products, specifically in the area of a new or improved methodology (Oates, 2005, Ch. 2). The product is a tailored SMO methodology that supports decision-making across multiple objectives within the WSC, while accounting for relevant uncertainties.

The practical progress steps, Figure 1.3 (in green), illustrate the sequential and iterative project stages involved in designing and formulating the methodology or artifact. The project steps are connected to the research questions in the flow diagram. The progress in the form of gained knowledge and research products is presented as responses from conference and journal articles and submitted manuscripts described in the lower section of Figure 1.3.

Table 1.1 outlines the connections between the articles included in the thesis to the three research areas described in Section 1.6.2 and the corresponding RQs. Detailed contributions related to the research areas and summaries for each publication are presented in Chapter 5, together with discussions about how they address the research questions.

Table 1.1. *Contributions of the dissertation and the linked research questions.*

Publication	RQ1	RQ2	RQ3	RQ4	Research area
Paper I		✓	✓		DES Robustness
Paper II	✓		✓		DES MOO
Paper III	✓	✓			DES MOO Robustness
Paper IV	✓		✓		DES MOO
Paper V	✓	✓	✓		DES MOO Robustness
Paper VI	✓	✓		✓	DES MOO Robustness

Paper I Experimental study, combining simulation and optimization, of weather variations' impact on deliveries in the WSC. Application of delivery performance objectives.

Author's contribution: Design of delivery performance objectives, compilation and analysis of results, and writing of the paper.

Paper II Framework integrating DES and multi-objective optimization (SMO framework) to calculate Pareto-optimal harvest schedules for delivery performance objectives. Customization of the multi-objective optimization algorithm.

Author's contribution: Design of the study, implementation and customization of the simulation-based multi-objective optimization framework, dashboard visualization, analysis, and writing of the paper.

Paper III Including a robustness objective in the SMO to handle delivery variations.

Author's contribution: Design of the robustness objective, implementation within the multi-objective optimization framework, analysis, and writing of the paper.

Paper IV Experimentation to improve the SMO framework methodology for many objectives, i.e., better performance for more than four objectives.

Author's contribution: Design and implementation of many-objective optimization, parallelization using cloud computing, analysis, and writing of the paper.

Paper V Suggest two metrics to identify and evaluate the robustness of harvest scheduling solutions under varying road accessibility scenarios.

Author's contribution: Design and implementation of customized multi-objective optimization, post-simulation analysis of multiple scenarios, and writing of the paper.

Paper VI A suggested framework using real-time data from a digital twin (DT), including an objective for CO_2 reduction, and methodology extensions to handle real-time variations in landings and road accessibility using artificial intelligence (AI) methods.

Author's contribution: Architectural design and writing of the paper.

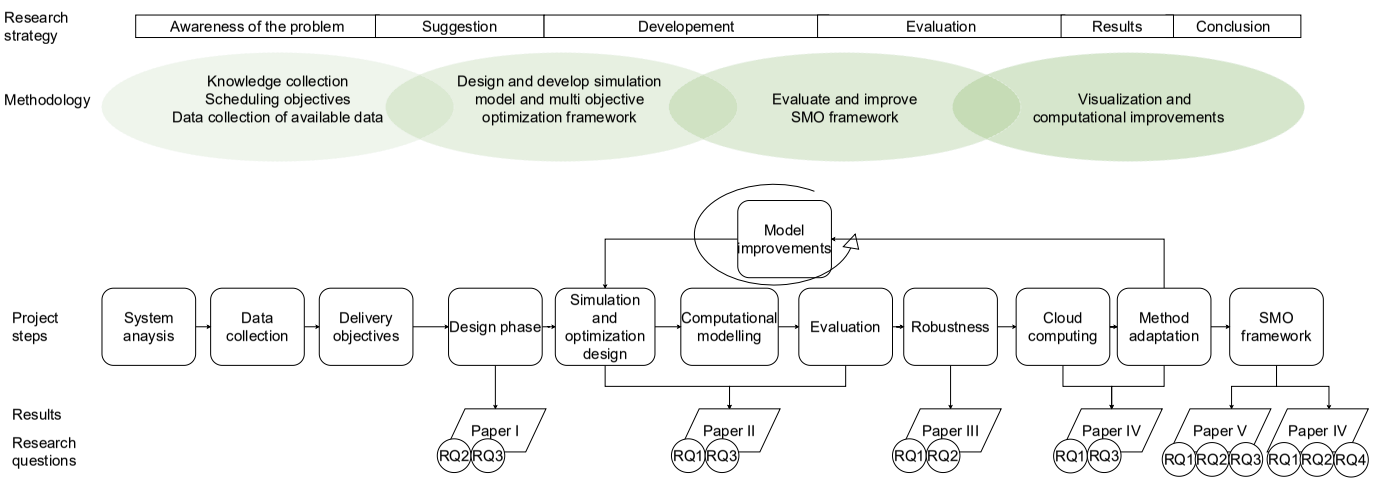


Figure 1.3. Research approach, methodology, practical project process, and outcomes.

1.8 Organization of the dissertation

The dissertation is organized as follows. In Chapter 2, a literature review is provided covering previous work and the current state of research related to WSC planning and scheduling. Chapter 3 presents the theoretical framework that forms the foundation of the research. Chapter 4 outlines the included publications and submitted manuscripts, concluding with a summary. Chapter 5 discusses the conclusions and contributions to knowledge regarding application of SMO in harvest scheduling under uncertainty, focusing on handling uncertain road accessibilty. Finally, Chapter 6 summarizes the research and proposes directions for future work.

2. Literature review

This chapter reviews simulation and optimization applications for WSCs. It presents objectives for customer delivery performance and their relation to multi-objective optimization. Variations and efforts to incorporate them into applications are reviewed and discussed in more detail.

2.1 Optimization applications in forestry supply chains

Mathematical optimization approaches have been well established in forestry since the late 1960s, and have been applied in planning and scheduling ever since (D'Amours et al., 2008; Epstein et al., 1999; Rönnqvist, 2003). Planning can be divided into forest management planning (Bettinger et al., 2007; Carle et al., 2021; Hyytiäinen & Penttinen, 2008; Wikström et al., 2011) and logistics and operations planning (Forsberg et al., 2013; Ghotb et al., 2024; Karlsson et al., 2006; Zamora-Cristales et al., 2015). Some examples of various approaches over time include Bettinger et al. (1997), utilizing Tabu search for harvest scheduling to optimize even wood flow with adjacency constraints and two wildlife habitat goals. Goycoolea et al. (2005) using linear programming for a spatial harvest scheduling problem applied to plan harvesting sites with spatial restrictions. Vila et al. (2006) apply mathematical programming to plan a logistic production-distribution network for the supply chain of the lumber industry. In Kogler et al. (2021), a mixed-integer programming model is used to compare, show the impact of, and find cost-saving strategies in the coordination of wood transportation.

These types of planning complement each other from a temporal perspective, where forest management plans have a very long-term perspective. In contrast, the supply chain planning time ranges from a few years to planning daily, ongoing operations, covering various aspects such as product selection, revenue maximization, and resource planning. Scheduling addresses periods from a year to monthly or weekly operations to differentiate the different time perspectives in supply chain planning. Hence, scheduling is the timing and sequencing of production and transport to meet customer requirements in a shorter time perspective.

Numerous papers have described optimization techniques adapted to solve procurement problems in the forest industry, involving customers (mills), supply, demand, harvesting, landings, road networks, and other related aspects. The different transport modes involved are typically truck, train, and boat,

and are traditionally the basis for formulating the optimization problem with objectives to minimize transport costs. There are also models that include the routing of trucks (Andersson et al., 2008) and harvesting teams (Bredström et al., 2010), as well as the optimal distribution of routes at harvest sites (Flisberg et al., 2007). Optimization techniques have the advantage of finding the exact optimality for a set of input variables. Most papers have been formulated as single-objective approaches, focusing on optimality in a single parameter. However, some papers have described optimization for multiple objectives, where multiple goals are transformed into a single unit and combined into one objective function, most commonly by minimizing a total cost. Nevertheless, focusing on one specific objective will exclude the impact of other objectives.

Different approaches are considered for incorporating uncertainty into supply chain modeling, including scenario-based modeling, sensitivity analysis, stochastic optimization, and robust optimization. In Shabani et al.'s (2013) review of studies using deterministic and stochastic mathematical models to optimize forest biomass supply, it implies that most studies have excluded uncertainty using the deterministic approach, except for a few examples. The authors also point out the one-sided focus on one objective, the dominant economic values, and that multi-objective approaches could incorporate more or other values, such as environmental and social values.

Shahi and Pulkki (2013) point out the gap in modeling techniques, specifically in the use of simulation-based optimization models to integrate supply and demand uncertainties. Both papers identify the interaction of simulation and optimization modeling as an underexploited possibility for future work, as well as the rare attempts to incorporate stochastic variations into the modeling. Recently, more papers have incorporated both simulation-optimization techniques and uncertainty, either as part of the work or as a primary focus. Shahi et al. (2018) integrate supply and demand uncertainties in a simulation-based optimization model to minimize the cost of the supply chain. Simard et al. (2024) integrate uncertainties in wood supply into a stochastic programming model for transport and production planning. Their results showed that the cost of uncertain supply ranged from 15–22% of the total planned costs, indicating that supply uncertainty incurs a significant economic impact.

Acuna et al. (2019) state that the use of simulation-based techniques in combination with optimization has been successful, particularly because it creates possibilities to include uncertainties in the WSC. Furthermore, the authors highlight that multi-objective optimization provides techniques to guide decision-makers in their management. This research gap gives opportunities to learn and develop simulation-based multi-objective models to enhance operations planning and control in the forestry industry. SMO can help foresters improve operational scheduling, i.e., maximize performance in multiple delivery targets. Incorporating stochasticity into the model can further reveal the effects of variations and how they influence optimal decisions, guiding forestry

in handling variations in reality, where decisions for delivery precision should be as close to optimal as possible.

2.2 Discrete-event simulation

Simulation involves developing a digital model that mimics the behaviors of an operational environment over time. It enables experimentation to study and analyze the behavior of systems for various scenarios without the need to interact with the actual environment. This is particularly useful when analyzing complex system relationships and dependencies, which are difficult to express as a function, making them challenging or even impossible to represent mathematically.

DES is widely used to simulate logistics and supply chains (Bottani & Casella, 2024). For wood and biomass supply chains, the extensive review by Kogler and Rauch (2018) reveals that many forest supply chain management research papers have employed DES to experiment with WSCs for various purposes. It is concluded that DES is suitable for analyzing operational and tactical logistics issues. Its strengths lie in its ability to map the complexity of the supply chain for decision support and answer "what-if" questions, thereby predicting supply chain outputs. A DES model can also help managers understand the complexity in supply chain relationships and interactions, which should not be underestimated (Kogler & Rauch, 2018). As inspiration for DES projects for the WSC, Kogler and Maxera (2025) highlight advances in the integration of Machine Learning techniques, where Reinforcement Learning is identified explicitly as handling an operational planning horizon for supply chains. In addition, they discuss how the integration of a DT can further drive the progress in decision support toward data-driven modeling.

2.3 Uncertainties and variations

Natural variations, including weather and heterogeneous raw materials, characterize the wood supply environment. Product outcomes, regarding quantity and quality, at sites most often vary from what is expected, despite pre-estimations based on forest data (Ene & Söderberg, 2021; Ene et al., 2021). Weather also has a significant impact on all activities in the WSC. Some examples include the effects on soil carrying capacity, fire hazards, and the risk of insect infestations at higher temperatures. Different strategies are developed to handle uncertainty in production outcomes. In the first stage, predict, with the greatest possible accuracy, the wood yield from the harvesting data, combined with different types of stand data for the sites (Ene & Söderberg, 2021; Ene et al., 2021). Another example is from Shavazipour and Sundström (2024), who address the uncertain production outcome in harvest scheduling using scalarized multi-objective

optimization and robustness metrics to handle uncertainty in harvest scheduling related to customer demand. The objectives are to minimize the differences between harvest production and customer demand, for each assortment and for different periods, where the production outcomes are uncertain.

To a great extent, road accessibility is affected by weather conditions. For smooth and timely deliveries, knowledge about landing inventories and accessibility to landings is crucial. The scheduling must be robust to accommodate variations, ensuring that a smooth flow of wood is delivered on time. A harvest schedule aims to synchronize production and transport with road accessibility, i.e., when there is sufficient road capacity to support transport to landings (Kuloglu et al., 2021). Although a feasible harvest schedule that matches supply and demand is possible, weather conditions can change and make roads inaccessible, variations that are crucial to consider when scheduling. Landing accessibility depends on the current weather situation and the weakest road accessibility class attained along the road. Along the transport route, the road is divided into segments with associated data on the segment of the road, such as road classification (Biometria, 2021). Each class gives the conditions for an accessible road segment, determined by the prevailing weather situation. For example, a *Class D* road is accessible only when there is frozen ground and when winter conditions prevail. Both *Class B* and *C* roads are not accessible during thawing conditions, and the *Class C* road is also not accessible during rainy periods. *Class A* roads are accessible all year round, making harvest sites along these roads prioritized to be saved for times of weather leading to reduced bearing capacity in other road classes. Road accessibility makes scheduling dependent on the prevailing weather situation at the truck's pickup time. A shorter period with reduced bearing capacity can also prolong the forwarding when landings are not emptied, allowing the replenishment of more forwarded wood.

In Larsson et al.'s (2016) literature review and interviews with staff in their study of supply management challenges in Swedish forestry, they conclude that risk management and resilience, based on evaluations of variations in WSCs, are rarely addressed in modeling. Additionally, the staff mentioned the lack of risk management tools during the interviews. Variations in the supply chain appear to be managed as they come, with most improvised solutions being based on managers' experience and skills. When road accessibility is suddenly limited, practitioners still attempt to manage deliveries according to the agreement and just-in-time principles. Some common and costly ways are to reduce truck loads, and redirecting transport to specific landings at night when roads are more likely to freeze. Other costly alternatives include unplanned reinforcement of roads with additional or coarse gravel to allow for truck transport or special trucks equipped with CTI (Central Tire Inflation), which reduces ground pressure.

In their review, Malladi and Sowlati (2017) focus on optimization approaches applied to operational forest transports. They discuss the problem of uncer-

tainties in forest transportation. They exemplify two uncertainty parameters —road closures and product availability —uncertainties that are often lacking in optimization models, as well as a focus on multiple objectives (accepting the heavily emphasized economic perspective). In summary, variations, such as accessibility to landings, should be incorporated into the modeling, and optimization modeling could benefit from involving more objectives that focus on values beyond monetary ones.

The WSC and its production and delivery depend heavily on the accessibility of roads (Hultqvist & Olsson, 2006). Accessibility, in turn, varies due to uncertainties in weather conditions and seasonal variations. Beyond current variations in accessibility, they are expected to increase further with a changing climate (Jönsson & Lagergren, 2017; Kellomäki et al., 2010; Lehtonen et al., 2019). This presents a challenge for managers when scheduling harvest operations to ensure a stable wood supply (Jönsson & Lagergren, 2017).

2.4 Simulation-based optimization

Applications of customized optimization models and methods increased in number during the 21st century (Acuna et al., 2019; D'Amours et al., 2008; Malladi & Sowlati, 2017). However, the combination of optimization and DES for WSC problems does not appear to have increased to the same extent. Only a few studies have combined optimization and simulation techniques for WSC planning problems (Kogler & Rauch, 2018), indicating that further research is needed. Examples of forestry or bioenergy supply chains applications are Shahi et al. (2018), who combine simulation and optimization, utilizing simulation-based optimization as a decision support tool for supply chain planning to minimize costs. The model also incorporates uncertainties related to demand and supply, as well as measuring backlogs. The model combines benefits with simulation, optimization, and uncertainty for the WSC, focusing on a single-objective total cost function aggregated from different costs. Akhtari and Sowlati (2020) use optimization for strategic-tactic planning of a bioenergy supply chain. The optimization, based on a mixed integer linear programming model, addresses different planning horizons for bioenergy and biofuel, while operational supply variations are managed within the simulation model. In the simulation, variations are captured at the operational level, which is used to adjust the tactical and strategical planning. Kogler et al. (2021) employs simulation and optimization to benchmark various strategies for wood procurement. Simulation is used to calculate the costs of different harvest systems to be used to optimize cost-efficient machine system configurations in fragmented boreal forests. Mixed-integer programming is used to cost-optimize harvest and transport planning of the WSC logistic (harvest and transport), both for separate actors and in combinations, to find the optimal setting when integrating multiple chains.

Although simulation alone is not an optimization tool, the DES can evaluate outputs that are difficult to calculate mathematically. Simulation is suitable for prediction, but not for finding optimal solutions, as simulations are inherently evaluative. Optimization, on the other hand, requires mathematical functions to calculate objectives, functions that can sometimes be challenging or even impossible to define. The output of supply chains is a typical example of such functions that are difficult to define. DES is suitable for exploring scenarios, and the combination of simulation and optimization is typically used to provide the simulation model with candidate solutions for evaluation. The combination of simulation and DES offers new approaches to generate meta-heuristically optimized solutions for complex problems, which cannot be achieved by simulation or optimization alone, but only through a combination of simulation and optimization. This combination is therefore well-suited to evaluate the supply chain output based on optimized harvest schedules for delivery performance.

2.5 Delivery performance measures

Stewart (1995) states the importance of delivery performance indicators:

> Delivery performance, the first key to supply chain excellence, is the driver of customer satisfaction that is most controllable by supply chain management (Stewart, 1995).

Larsson et al. (2016) conclude from literature reviews and interviews with staff at Swedish forest companies that few studies have presented performance indicators for wood supply. In addition, existing performance indicators primarily focus on cost minimization or profit maximization in optimization-solved planning problems for various optimization problems.

Gunasekaran et al. (2004) discuss different performance measurements in supply chains, where the common factor for all supply chains is that the measure must be able to assess the organizational performance of a specific value chain. Delivery targets may vary depending on which stakeholder in the WSC defines the targets (Forslund & Jonsson, 2007). For a harvest team or transport company, this could involve maximizing the utilization rate while minimizing labor costs simultaneously. From a forest owner's perspective, this could include maximizing net revenue per cubic meter while simultaneously minimizing damage from transports on roads or forest land. Hence, delivery performance varies depending on the context of the value chain. Gunasekaran et al. (2004) also define and rank the importance of delivery performance measures from the perspective of customer value. The quality of delivered goods, on-time delivery of goods, and flexibility of service systems in meeting customer needs are ranked as highly important due to their connection to the customer value of the products. Customers in the WSC require smooth and

timely deliveries to reduce the risk of a standstill in the mill or production. Here, the quality of the wood is a key factor, where the production is based on the same, even quality.

Delivery performance in the WSC requires measures that describe how operational decisions affect deliveries and the value of delivered products. Pound et al. (2014, Ch. 3) define lead time as the time required to complete the delivery of a product, and backlog as the quantity of ordered products that are currently late. For value chains, but especially order-to-delivery value chains, lead time and on-time delivery are defined as key performance metrics (Forslund et al., 2009). The wood products have freshness requirements; to qualify for a product segment (Biometria, 2025) there should be, e.g., no blue stain in pine saw logs or fresh pulp wood for easy debarking. Kogler and Rauch (2023) examine the relationship between lead time and loss of sawlog value, showing that the total lead time of a product is significant in determining whether a product will be downgraded to a less valuable product. The authors also discuss the importance of coordinating harvesting and transport to reduce the total lead time from harvesting to delivery. Better scheduling can help reduce value loss, emphasizing the need to incorporate lead time into future models. The lead time in wood supply is both a quality indicator (Kogler & Rauch, 2023) and a measure of the efficiency of harvest scheduling, defined as the time needed to complete the delivery of a product (Pound et al., 2014, Ch. 3). Lead time and backlog objectives are generally conflicting. Reducing the risk of significant backlogs often requires larger wood volumes in landings, which increases the average lead time.

In addition to these objectives, as in most supply chains, performance is often evaluated based on production throughput, defined as the number of entities processed per unit time (Hopp, 2011, Ch. 4; Pound et al., 2014, Ch. 1, 4). This reflects the overall efficiency of the supply chain and serves as a measure of its productivity. Consequently, from a customer-focused logistics perspective, the lowest common denominator of delivery performance in a general WSC is formulated by lead time, backlog, and the number of cubic meters delivered per hour: minimizing lead time, minimizing backlog, while maximizing throughput simultaneously.

2.6 Multi-objective optimization

Optimization involves maximizing or minimizing one or more objectives, with single-objective optimization being the most common approach focused on evaluating a single objective. These problems often have a clear aim: to determine the optimal input variable setting that yields the best (one) solution. However, real-world problems usually involve multiple objectives, which may also be in conflict with one another resulting in a multi-objective problem. An example of a multi-objective approach is presented in a recent publication by

Nabhani et al. (2024), who address a complex problem of optimizing sustainable forest management while considering three objectives simultaneously: timber supply, climate change, and biodiversity conservation. This study utilizes the epsilon-constrained method (mixed-integer programming). Another example is Fang et al. (2025), who employ weighted multi-objective fuzzy chance-constraint programming to evaluate land suitability for a biorefinery, optimizing economic, environmental, and social objectives concurrently. These objectives include bioethanol production costs, carbon emissions across the supply chain, and job demand for biorefineries.

As introduced in Chapter 1, a common strategy in multi-objective optimization is to convert the problem into a single-objective one by mathematically combining the objectives, often through a weighted sum (scalarization). This allows for the use of standard single-objective solution methods. A typical case is the optimization of economic performance by aggregating various cost components into a single objective function that weights the individual costs. However, this approach requires assumptions about the objectives in advance, which introduces the risk of bias in both the optimization process and its results. It also relies on the assumption that all objectives are expressed in the same unit and scale, allowing them to be aggregated into a single function where the predefined weights determine the relative importance of each contributing objective. Conversely, multi-objective optimization can accommodate simultaneous goals expressed in different units and provide insights into trade-offs between them, without requiring parameter or unit conversions. Examples of such distinct objectives include timely deliveries and lead time, where trade-offs are guided by customer preferences. A longer lead time in the WSC context may indicate a more agile logistics chain, capable of avoiding backlogs. However, this also poses the risk of extended storage times, which could potentially compromise product quality. Approaches for multiple objectives are necessary to handle multiple objectives for customers' delivery performance. Achieving a more balanced and context-sensitive evaluation requires explicit modeling and consideration of multiple objectives. To do this, more objectives need to be modeled simultaneously, and the inclusion of uncertainties is stressed.

This is also aligned with what Acuna et al. (2019) state, that SMO could support managers in decision-making when analyzing decisions involving multiple objectives. Atashbar et al. (2016) call for more studies, both at the operational level for the biomass supply chain and in models targeting multi-objective objectives. The combination of simulation and meta-heuristics within multi-objective optimization provides techniques to handle variations in the WSC, thereby converging to more optimal decisions in scheduling, planning, and management.

Over the past two decades, extensive research has been conducted on multi-objective optimization methods, with numerous supply chain applications identified (Aslam et al., 2011; Rahimi et al., 2022). However, few studies have formulated harvest scheduling problems in the context of multi-objective

optimization using meta-heuristics, particularly where attention is paid to uncertainties affecting delivery performance in wood supply. Only recently, Castro et al. (2024) published a paper utilizing the meta-heuristic NSGA-II (Deb et al., 2002) to optimize spatial forest management with two objectives: maximizing harvested volume and minimizing the standard deviation of the harvested volume. The authors emphasize the importance of customizing the algorithm and highlight the potential of the method, presenting it as a promising and user-friendly tool for forest planning.

2.7 Multi-objective decision support

As the problem grows in complexity —both in the number of objectives and the incorporation of uncertainties —it becomes increasingly difficult to identify a single, exact plan that holds. This underscores not only the need to consider different sets of input parameters, but also that the final decision regarding optimality ultimately rests with the decision-maker. This is common in meta-heuristic methods, such as genetic algorithms. In these approaches, different input sets are tested to produce various outputs, aiming to find approximate solutions, or the best rule of thumb. This process typically involves a decision-maker.

A genetic algorithm (Lambora et al., 2019), particularly in multi-objective optimization, searches for a diverse set of solutions along the Pareto front, without requiring the objectives to be combined into a single aggregated function. In comparison to an optimal solution, genetic algorithms do not weight the objectives but provide a Pareto front with trade-off solutions among the objectives, allowing a decision-maker to make a choice. Genetic algorithms enable decision-makers to explore trade-offs between conflicting objectives by maintaining a population of solutions, rather than collapsing all information into a single scalar value. This enables a flexible and transparent evaluation of multiple priorities, especially when the importance of objectives is difficult to quantify or may change depending on the context.

2.8 Research gap and motivation

In Bettinger and Boston's (2017) paper, which includes research recommendations, the authors evaluate heuristics in general as an alternative for forest planning. They divide the heuristics into two groups: *s*-heuristic (providing one solution), where the development of one plan is further improved by single-objective heuristics, and *p*-heuristics (providing a population of solutions), for applicable population-based heuristics. In their conclusion, the authors discuss their findings with an audience at the IUFRO 125th Anniversary Congress in Freiburg, Germany in 2017, and asked the audience what the benefit might be

of using meta-heuristics to address adaptive forest management. Based on the audience's answer, the authors acknowledge that forest management planning can be addressed successfully using heuristics in the same manner as exact approaches have been. In particular for complex problems, when it can be challenging to find a single optimal plan.

This conclusion aligns with the identified research gap in developing a methodology for scheduling harvesting for multiple objectives. It provides a set of solutions aimed at improving delivery performance through the use of meta-heuristic genetic algorithms. Harvest scheduling is the starting point of the supply. Road accessibility and delivery variations are highlighted as critical factors for smooth deliveries, where robustness in scheduling is essential. In addition to serving as a decision support for forest managers, more objectives should be considered, allowing managers to evaluate trade-offs among them. Hence, a framework is proposed for delivery performance decision support with multiple objectives.

This research gap highlights an intersection between different research areas. The key research areas involve using DES in combination with optimization, where multi-objective optimization can provide solutions that ease trade-offs between objectives for decision-makers. For greater reliability in deliveries, accessibility to the landings is crucial, and methods to handle and evaluate accessibility to the road in scheduling are necessary. Additionally, to support the development of real-world decision-making tools, suggestions for result visualizations can help stakeholders understand the potential applications of the tool more intuitively.

3. Frame of reference

In this chapter, SMO as a decision support method and its theoretical framework are discussed. The chapter also introduces the need for computational resources and methods to speed up the calculations, along with some suggestions of tools for a visualization layer applied to the SMO framework.

3.1 Multi-objective optimization methods

Figure 3.1 shows a rough breakdown of the optimization taxonomy, where the first division is between deterministic (classical approaches) and meta-heuristic approaches. Deterministic methods ensure the same output for the same input and can effectively find an exact and optimal solution (in unrestricted solving time) for a well-defined problem. Examples of methods include linear programming, non-linear programming, and mixed-integer non-linear programming.

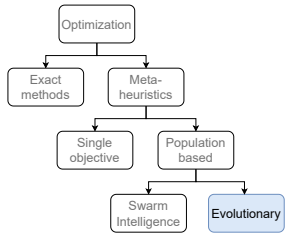


Figure 3.1. Rough division of optimization methods.

However, for complex problems where it is difficult or even impossible to find one optimal solution, meta-heuristics serve as an alternative. The main methodology in a heuristic method is the iterative search for increasingly better solutions to refine the solution or solutions. Compared to deterministic methods, they do not guarantee mathematical optimality but rather adequate solutions to imperfectly defined optimization problems, which are often good enough in practice (Talbi, 2009). Supply chain problems with their complexity, where all input parameters can be cumbersome to define or provide exact data for, are typical of meta-heuristic approaches. Meta-heuristics can be designed as single-objective or multi-objective problems (Boussaïd et al., 2013), where both methods have strengths that depend on the problem description. In the single-objective approach, different objectives are mainly combined into one single-objective function using scalarization. However, scalarization needs to be set adequately, as the objective functions are highly affected by the weights (Konak et al., 2006). The results are shown in one objective, often using the same (monetary) unit without possibilities for comparison between the objectives, such as lead time versus backlog. In real-world supply chains, the ability to prioritize objectives such

as delivery targets is vital in decision-making, which is possible using Pareto front solutions (Konak et al., 2006).

Multi-objective problems can be divided into non-population-based, less common, and population-based methods. In the population-based approach, a set of solutions is calculated and presented as a Pareto front in the decision space. The Pareto front shows the objective values for all solutions simultaneously, where no objective can be improved without worsening at least one other (non-dominated solution). The Pareto solution allows the comparison of objectives with respect to their objective values, and where trade-offs in the objectives can be compared and prioritized. In turn, population-based methods are classified by search strategy into swarm intelligence and evolutionary approaches. Evolutionary approaches have long been applied to real-world problems, where trade-off decisions must be made (Konak et al., 2006). A large number of articles can be found in which evolutionary algorithms, in particular genetic algorithms, have been successfully implemented in planning and scheduling problems. In Rahimi et al.'s (2022) extensive review of multi-objective optimization algorithms, the authors conclude that genetic algorithms have been dominant in planning and scheduling problems since 2014, where NSGA-II is the algorithm most often applied.

3.2 Simulation-based multi-objective optimization

In multi-objective evolutionary optimization, a population of solutions is iteratively calculated and refined for more optimality until finding a solution set with Pareto optimality. A Pareto solution is not one best solution, but rather one out of many solutions. The fitness values, or objective values, for the best solutions are shown as the Pareto front in the objective space, to the right in Figure 3.2, for the Pareto solutions, to the left in Figure 3.2. Choosing what solution is preferable on the front is for a decision-maker to prioritize. In complex problems, where the objective functions can be both non-linear, difficult, or impossible to develop or determine, simulation is an enabler for multi-objective optimization. Tordecilla et al. (2021) identify simulation-optimization methods suitable to handle both uncertainties in the simulation, where optimization provides the simulation with better or optimal scenarios to analyze. The authors also conclude that the most prevalent minimization objective is cost minimization, and they call for other, multiple objectives and meta-heuristic methods in combination with simulation, suitable for real-world problems with uncertain parameters. The authors consider meta-heuristic methods to still be scarce for simulation-optimization problems in supply chain networks.

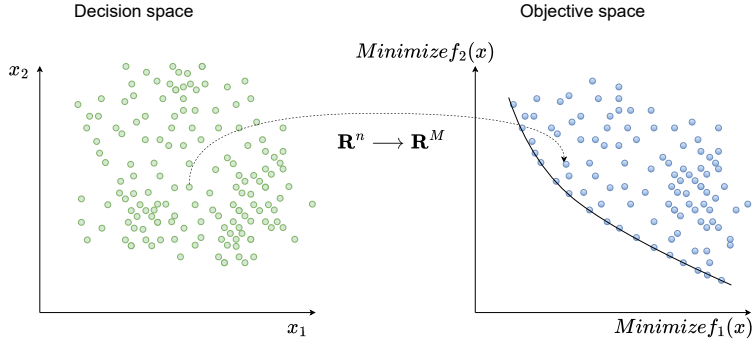


Figure 3.2. Pareto front with a good diversity for two objectives.

3.2.1 Genetic algorithms

Multiple objectives are involved when scheduling for delivery performance. Meta-heuristic methods find strategies, as rules of thumb, designed to efficiently find sufficiently good solutions, especially when exact methods are too slow or infeasible. Heuristics are problem dependent, while meta-heuristics are problem independent, providing general approaches that can apply to a broad range of problems. Metaheuristics are particularly effective for solving complex, non-linear optimization problems with large or poorly defined search spaces, where exact methods are computationally impractical. While they do not guarantee optimal solutions, they can often find high-quality solutions efficiently relative to problem complexity. There are many meta-heuristic methods, and the hierarchy is shown in Figure 3.3. However, the genetic algorithm has long been used particularly for scheduling problems, such as the Traveling Salesman problem (Larrañaga et al., 1999) and supply chains in general (Aslam et al., 2011).

To find the best trade-off solutions for multiple objectives, multi-objective optimization methods have been used extensively (Sharma & Chahar, 2022). Among these, multi-objective evolutionary algorithms (MOEAs) represent the category of solution methods inspired by nature. For multi-objective scheduling problems, meta-heuristics using evolutionary algorithms are found to be a powerful method. Some of the most well-known methods are strength Pareto evolutionary algorithm-2 (SPEA2), multi-objective evolutionary algorithm based on decomposition (MOEA/D), non-dominated sorting genetic algorithm II (NSGA-II), and non-dominated sorting genetic algorithm III (NSGA-III) (Sharma & Chahar, 2022).

As shown in several publications summarized by Rahimi et al. (2022), genetic algorithms, notably the non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al., 2002), are generally the most popular and particularly successful for scheduling problems. NSGA-II (Deb et al., 2002) has been used for the past two decades for its efficiency in solving various types of

problems (Verma et al., 2021). Therefore, NSGA-II is particularly well suited for applications to the combinatorial scheduling problems of supply chains.

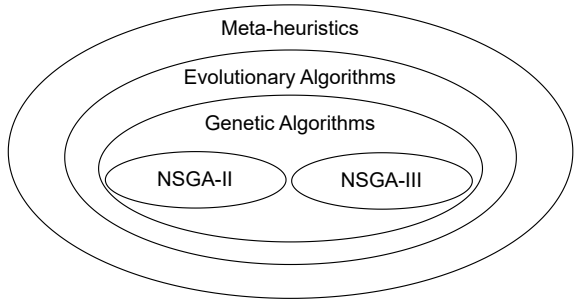


Figure 3.3. Description of relations between the described meta-heuristics.

3.2.2 NSGA-II

MOEAs aim to find a representative set of nearly Pareto-optimal solutions, or trade-off solutions, with good diversity over the front to provide the decision-maker with different choices. The algorithm consists of evolutionary steps, where for each generation a population of various solutions is evaluated and improved for the next generation using non-dominated sorting (NSGA-II elitist in Figure 3.4). The elitist operator preserves non-dominated solutions in the population with the best rank and diversity (Deb et al., 2002), where it calculates the crowding distance (distance to other solutions) for the solutions closest to the optimal front to ensure a spread across the objectives. As shown in Figure 3.4, starting from an initial population of solutions, each individual's fitness is evaluated based on the objective functions. The solutions are then ranked and sorted according to their fitness values. The best-performing solutions are selected to generate a new population. The evolutionary process involves selection, crossover, and mutation, where new offspring (children) are created from the parent population inspired by evolution to form the next generation.

The multi-objective WSC problem can be interpreted in the multi-objective optimization formulation. For a general continuous multi-objective optimization problem, the canonical form is written as:

$$\begin{aligned} \text{Minimize} \quad & f_m(\mathbf{x}), && m = 1, \ldots, M \\ \text{subject to} \quad & g_j(\mathbf{x}) \geq 0, && j = 1, \ldots, J \\ & h_k(\mathbf{x}) = 0, && k = 1, \ldots, K \\ & \mathbf{x}^L \leq \mathbf{x} \leq \mathbf{x}^U \end{aligned}$$

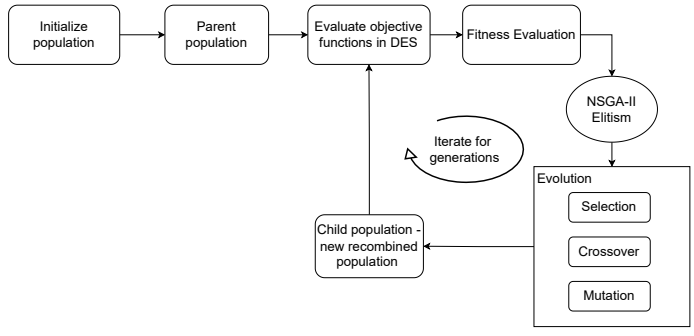


Figure 3.4. Conceptual description of NSGA-II in combination with DES.

where $x \in \mathbb{R}^n$ is an n dimensional variable vector, M objective functions to minimize (or maximize) under J inequality and K equality constraints. For the solutions in the solution vector $\mathbf{x} \in S$ following applies. For any $\mathbf{x_1}, \mathbf{x_2} \in S$, the solution $\mathbf{x_1}$, is said to be dominant over $\mathbf{x_2}$ if an only if:

- $f_m(\mathbf{x_1}) \leq f_m(\mathbf{x_2}) \; \forall \; m = 1, \ldots, M$
- $\exists \; j$ such that $f_j(\mathbf{x_1}) < f_j(\mathbf{x_2})$,

i.e, $\mathbf{x_1}$ is not worse than $\mathbf{x_2}$ in any of the objectives and $\mathbf{x_1}$ is better than $\mathbf{x_2}$ in at least one of the objectives

For less complex systems, the objective functions can be traditionally mathematically defined to evaluate the fitness of the objectives (calculate objective values). For multi-objective problems with complex objective functions difficult to model by functions, which is the case for supply chains, optimization is combined with simulation to evaluate fitness values (Branke et al., 2008; Hunter et al., 2019) referred to as an SMO. Simulation is a powerful tool for evaluating complex supply chain outputs, assessing each objective function's fitness and constraining the supply problem. The objective functions are evaluated in the DES "outside" the optimization, where inputs to the DES provide the multi-objective optimization with multiple outputs, making it possible to calculate objectives, Figure 3.5. The setup and details of an SMO are further expanded in Paper II, Section 4.2.

3.2.3 Operators

Genetic algorithms are inspired by the ideas of natural evolution, represented by the search for iteratively "genetically" modified and improved solutions based on the idea of survival of the fittest. Genetic algorithms search iteratively for a refined population of solutions using the operators: selection, crossover, and mutation. Customizing an algorithm's operators for a specific problem is key to

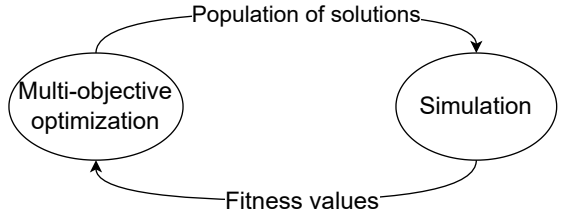


Figure 3.5. Relation in an SMO.

guiding it toward effective optimization. The operators select the best solutions to be combined in new and refined solutions using crossover and mutation. In a successful operator customization, the diversity and spread are maintained for the Pareto front, where the solutions cover the front with a good spread and improve upon the solutions from the previous generation of the population.

The selection operator selects the solution with the best fitness values in the parent population. This can be done by random selection or the proven effective Tournament selection (Miller, Goldberg, et al., 1995; Zhang & Kim, 2000). In tournament selection, parents with the best fitness values are selected to be the parents of the new children. The children, in turn, are created by the parents, and the sequences in the solution vectors are changed to new patterns determined by the crossover and mutation operators, to resemble evolution, suitable for the problem.

There are many defined crossovers, in particular, and mutation operators defined for diverse problems over the years, where further customization for problem type can improve convergence and diversity among solutions. However, the harvest scheduling problem, like many planning or scheduling problems, is a combinatorial permutation problem where each site can only be harvested once, and where the order matters. Continuous problem operators are not applicable but must be customized. The harvest scheduling problem is remarkably similar to the Travelling Salesman Problem, where there are crossovers and mutation operators that have been proven to have good properties for permutation problems (Larrañaga et al., 1999, Ch. 5; Haupt & Haupt, 2008). More details concerning customized crossovers and suitable mutation operators for the harvest scheduling problem are further explored and described in Paper II, Section 4.2.

3.2.4 NSGA-III

Multi-objective problems are considered to have fewer than four objectives, whereas many-objective problems have four or more. Although NSGA-II is an effective algorithm for three or fewer objectives, it remains as an alternative for more objectives. However, with increasing parameters, there are more effective

alternatives. The sequel to NSGA-II is NSGA-III (Deb & Jain, 2014), which has been proven effective for more than three objectives.

NSGA-III requires a defined reference direction in the objective space, Figure 3.6, pointing out search directions for a better spread of the Pareto front. First, solutions are selected in the reference directions, and then solutions with the smallest perpendicular distance to the reference directions are selected to ensure good coverage in spread and diversity of the Pareto front.

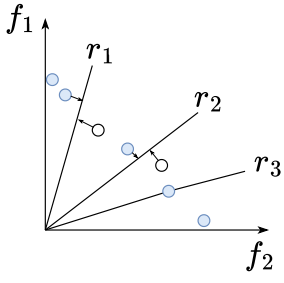


Figure 3.6. NSGA-III and reference directions $r_1\, r_2\, r_3$.

Sampling search directions can be accomplished in different ways, with two standard methods being Minimal Riesz Energy sampling (Hardin & Saff, 2005) and the Das-Dennis method (Das & Dennis, 1998), which is the most widely used approach for sampling search directions. In Das-Dennis, the reference vector starts from the origin in the direction of the points, where the number of points divides the Pareto front into partitions to obtain an even spread. Thus, when handling many objectives, the problem needs to be initialized in relation to where and how to search for solutions, where the reference directions are placed as normalized search direction vectors for the objectives (Deb & Jain, 2014). The search directions are defined on a unit simplex, where the weights of the reference vectors are defined as $\sum_{j=1}^{M} \omega_j = 1, j = 1, \ldots, M$. Each search direction is divided into steps to cover the path in that direction. This way of guiding the algorithm makes NSGA-III more efficient than NSGA-II in handling many objectives. The bottleneck is that the search direction, along with its steps or partitions, is linked to the population size. A larger population size, in turn, leads to significantly higher computational time and cost. As an example for a problem with four objectives, $M = 4$ and seven or eight partitions, $p = 7$ or 8, which is considered moderate, the number of points defined by *reference points* $= \binom{M+p-1}{p}$ in the population must be at least the same number:

- $M = 4,\ p = 7 \rightarrow 120$ in the population
- $M = 4,\ p = 8 \rightarrow 165$ in the population

As the number of partitions in the solution space increases, the required population size grows rapidly and becomes computationally demanding. An approach to handling this is further described in Section 3.4 and Paper IV, Section 4.4, where the computational setup and computer capacity can improve solution time, which is crucial in applications.

3.3 Robust design

A robust design concept was first introduced by Taguchi (1987) to control variations and uncertainties in a production environment rather than focus on the uncertainties themselves. Sanchez and Sanchez (2020) discuss and define the goals for a robust design as a design that yields insight into what drives system performance, and focuses on practical and controllable factors for decision-makers. The authors identify a robust design as one that contribute to better implementations in real-world settings, identifying and controlling factors that affect the performance. They also conclude that for a design to be robust, it should be integrated into the simulation-optimization, where optimized solutions should remain as insensitive to input changes as possible for robustness, also called robust optimization.

Minimizing backlog addresses the total annual delivery, but to manage delivery deviations during the year, another objective that targets monthly delivery fluctuations is necessary to ensure even flows. The objective should minimize monthly delivery deviations and ensure that deliveries are even, because even wood flows are critical and demanded by customers. This calls for a robust design of the SMO. One way of approaching robustness in the design is by the objectives, using an objective in the SMO to minimize the delivery variation as a loss function. Sanchez and Sanchez (2020) propose a loss function to capture variations, where the expected loss is defined by $E[\iota_{Y_x}] = \sigma^2_{Y_x} + (E[Y_x] - \tau)^2$. Interpreted to address the monthly delivery fluctuations, Y_x is the simulated deliveries for solution x, where τ is the demand for the month, i.e., the sum of variance in delayed deliveries and the square of the size of the deviation in deliveries. The loss function aims to incorporate delivery deviation in both the mean value and the standard deviation between months. In Paper III, this is described in more detail in Section 4.3.

Variations in accessibility to landings are identified as a severe limitation in harvest scheduling (Section 2.3), and predicting what accessibility conditions prevail. Accessibility as a variable should be reflected in the simulation model, as this is a limiting constraint for transportation at certain times. Specifically, weather-dependent road accessibility, accessible or not, must be reflected in the DES. This limitation will affect the DES output results for the objectives' fitness values. Robustness in scheduling means that a scheduled plan should be feasible even if variations in road accessibility occur. When weather affects road accessibility and limits accessibility to landings, backlog and lead time increase due to delayed deliveries and volumes being trapped at landings.

One might think that the policymaker would want to know how robust the Pareto-optimal harvest schedules are for weather variations and whether some solutions are better. It can be valuable to evaluate the robustness of different solutions, using metrics that capture performance across varying weather and road accessibility scenarios. The decision-maker will be involved with knowledge of both acceptable trade-offs in the objectives and will decide

on "how much robustness is it worth," leaving it to the decision-makers to evaluate a set of Pareto-optimal solutions for different weather scenarios. Hence, the decision-maker takes on more decision-making where their knowledge of expected road accessibility scenarios and their prioritizing of objectives play a more critical role.

A harvest schedule can be stress tested for a set of road accessibility scenarios to identify a robust solution, which is helpful for decision-making under deep uncertainty (Lempert et al., 2006). In deep uncertainty, probability distributions of possible events, such as road accessibility, are lacking. Access to roadside landings can be viewed as deeply uncertain due to many possible accessibility scenarios over the scheduling horizon. Pareto-optimal schedules can be evaluated for a variety of alternative road accessibility scenarios (Lempert et al., 2006; Shavazipour et al., 2021), where robust solutions should showcase the same delivery performance for a variety of accessibility scenarios. This approach has been used for robust decision-making under deep uncertainty for supply chain problems (Kwakkel et al., 2012; Shavazipour et al., 2020) and forestry management (Knoke et al., 2025; Radke et al., 2020; Shavazipour & Sundström, 2024; Shavazipour et al., 2022).

Two common categories of metrics are *regret-based metrics* and *satisfying metrics*. The regret-based metric, or maximum regret, measures the deviation from optimal performance (Eker & Kwakkel, 2018), and the satisfying metric measures the domain criterion (Starr, 1963), describing the share of scenarios that satisfy certain conditions, which can be interpreted as given thresholds for the objectives. The robustness metrics, maximum regret, and domain criterion provide a quantitative measure of how robust each solution is for a set of (uncertain) scenarios. This approach to testing schedules for weather scenarios is described in Paper V in Section 4.5.

3.4 Computational cost

A known bottleneck for meta-heuristics is their time-consuming nature and high computational cost (Sharma & Chahar, 2022; Talbi et al., 2008). The search for Pareto-optimal solutions often involves exploring large populations, as in genetic algorithms, which can require significant computational resources and time—especially when many generations are needed. For example, when applying NSGA-III (as previously described), computational time and cost increase as the population size grows and more search directions are considered.

Many studies have proposed reducing computational time by customizing how the algorithm is guided, such as through surrogate modeling. As early as 2008, Talbi et al. (2008) proposed strategies to organize computations, including the use of parallel and distributed computing to improve solution times for genetic algorithms. Genetic algorithms are generally time-intensive; however,

their population-based structure is well-suited to parallel computing, allowing fitness values to be evaluated simultaneously.

Parallelizing computations is particularly well-aligned with genetic algorithms, where a population matrix can be distributed either across separate machines or, more commonly today, across on-demand computing cores, enabling parallel fitness evaluation. How this setup can be applied to the SMO framework is explored further in Paper IV and described in Section 4.4, where the problem is configured for parallelization on a virtual on-demand computer.

3.5 Artificial intelligence and digital twin

As outlined, a robust design is suggested to handle supply chain uncertainties in the SMO. Nevertheless, sudden real-time changes in production or landing accessibility are difficult to adjust for, despite having a robust design in the long-term operational schedule. Adjusting the schedule for uncertainties in a real-time scenario requires another approach, pushing the robustness criteria further. Transportation is particularly focused on changes in prerequisites. A schedule is not an operational plan, but a long-term strategy that managers try to stick to by managing anomalies as they occur. Palander et al. (2024) bring attention to the effects of weather when modeling forest transportation, where the data mainly focus on broadly available data that may underestimate essential factors in modeling. A typical example of where scheduling adjustments happen is the dispatch of trucks. In other words, when x trucks are available, the actual landing inventories are uncertain, and the weather forecasts suddenly change for next week, which truck should transport what products from where, and to what customer, to adjust the transports to the delivery performance goals?

In Touloumidis et al.'s (2025) review of weather-related disruptions (mainly rainfall and snow), the authors emphasize the data-analytic approach in logistic systems, highlighting real-time data and AI methods to adjust transportation routing based on weather forecasts. Karkaria et al. (2025) focus on using DTs for optimization in manufacturing systems, enhancing operational strategies through dynamic improvements. A DT of the system allows for real-time updates, captures real-world situations, and makes it possible to manage uncertainties in the system. It is further used in predictive analysis. They conclude that optimization based on offline and online data, integrated by a DT, enhances decision-making, adapting to new situations. One of the methods discussed (Karkaria et al., 2025) to enhance the value of a DT is reinforcement learning (RL), where an agent learns how to adapt complex and large systems from the DT data.

RL, an AI method, could be supportive for this purpose, to adapt the scheduling in the dispatching of trucks to follow the settled plan and target the delivery performance objectives. RL is used to solve many supply chain management problems for different objectives (Rolf et al., 2023), for adaptive decision-

making learning where decisions are the most rewarding. The agent, or "AI decision-maker" (Figure 3.7), uses iterative trial-and-error, learning what decision is more optimal than others, where the output is a reward $R(s_i, a_i, s_{i+1})$, a_i is that action taken (dispatching), s_i the state of the environment (WSC) and s_{i+1} the next state (Gosavi, 2015, Ch. 4). RL is a data-driven method, which learn by collecting maximum rewards from new decisions, independent of historical input data. Learning is about predicting the outcome from a data set provided to the RL model (Greasley, 2019) and can be described as a scheduled decision process, where a decision to take an action affects the output and state of the system, now and in the future (Sutton & Barto, 2018, p. 47).

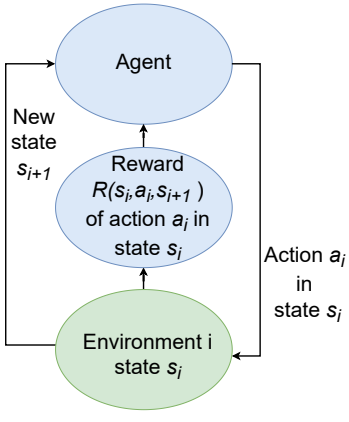


Figure 3.7. The agent interacting with the environment's state, resulting in a certain reward.

RL primarily relies on real-time data to adjust a plan momentarily in response to prevailing conditions in the supply chain. Most simulation tools are based on historical data, disconnected from real-time updates (Taylor et al., 2021). However, when training the RL agent in an offline environment using a simulation environment, it is beneficial to start the time-consuming training offline to better utilize real-data linkage for fine-tuning and adjusting the agent's decision-making (Yan et al., 2022). Although the offline environment is used for RL training, the final goal is to transfer and implement RL in a real-world environment, such as a DT. A DT can be described as a concept to mirror a real-world environment into a meta-model, for experimentation and modeling (Grieves, 2023). A DT is typically incorporated into an optimization or simulation model to analyse effects based on real-time status. The combination of a DT with an RL agent, able to adjust parameters to adhere to the scheduling, can be used to prescribe operational actions to "stick to the plan". To conclude, simulation-based optimization models can be improved by RL for real-time scheduling and adaptive data-driven decision-making, and further adapted to relevant real-world supply chain data (Chen et al., 2024) to improve delivery performance. This can be used to adjust transportation (and operations) in the supply chain, based on data from weekly weather forecasts (Väätäinen et al., 2025) and information on products at landings, to respond to short-term changes to adhere to established delivery goals.

3.6 Dashboard prototype

In multi-objective optimization, trade-off decisions between multiple simultaneous goals must be made. The same applies to deciding which solution is robust enough when analyzing solutions for variations of road accessibility scenarios discussed in Section 3.3. The decision-maker with knowledge of the supply system should make these decisions. An example can be to decide which delivery performance objectives are of greater importance than others as a decision rule. The Pareto front offers multiple solutions for the scheduling, where each solution has an unavoidable trade-off in prioritizing the objectives. To make a well-informed decision, visualization of, for example, results from SMO or simulation results can guide a decision-maker in selecting options for scheduling, even if the research of Kivikangas et al. (2025) indicates that increased effort is required of decision-makers as the number of objectives grows.

One advantage of DES is that it is helpful not only for fitness evaluations, but also for simulating the supply chain for specific solutions. It offers the possibility of post-processing. For example, it can analyze a particular solution to provide more details in processes and at various times, as well as the robustness to changes in settings, such as road accessibility scenarios. Simulations of solutions, with the possibility to change scenarios in DES, can provide more detailed information about robustness to uncertainties and offer a more nuanced resolution. A dashboard that visualizes current performance objectives and allows one to experiment with solutions can guide decision-making to result in better informed decisions. An example of such an experimentation dashboard is shown by Fjeld et al. (2024). This dashboard is designed for experimentation, allowing students to learn and practice decision-making in the WSC for delivery performance. The tool and dashboard enable students to experiment with operational supply chain planning for harvesting teams and trucks, ensuring deliveries are fulfilled under road restrictions. Visualization for decision support is a major research area itself, but SMO-based models can benefit from being visualized in what is referred to as a dashboard prototype. This also serves as a bridge between research and applications, as it represents the first step toward a practical and applied decision support tool. The intention of visualization of the models is to shorten the steps to commercialization by adding a layer "on top," where experimentation is allowed for a decision-maker. It is also aligned with the idea of the DSR approach, to take research (artifacts) closer to practitioners, which is pushed a bit further by adding an artifact (SMO model) in an application. Examples of dashboard prototypes are visualized or proposed for the models in Paper II (Section 4.2), Paper V (Section 4.5), and Paper VI (Section 4.6).

4. Results

This dissertation partly addresses the limitations and unresolved questions identified in the EU project Multistrat ERA-NET (Horizon 2020) and the subsequent project GreenLane between January 2019 and June 2022. The project aimed to synthesize best-practice guidelines on managing wood supply, primarily using simulation-based methods. The modeling was introduced for three different contexts, weather and WSCs, in Sweden, Austria, and Norway, with varying conditions due to geographical perspective. All countries' WSCs struggle with delivery challenges, mainly caused by expected and unexpected seasonal variations. More information on the project can be found on the GreenLane project webpage.

In the project, models were developed to enable value tracking of responses to delivery variations in WSCs caused by challenging weather scenarios. This ultimately revealed a multi-objective supply problem, where the objectives may be concurrent, and variations in weather have been found to impact deliveries significantly.

The dissertation has followed an iterative path in which new knowledge has been added to previous studies, as shown in Figure 4.1. The primary objective is to develop a methodology for handling multiple objectives in WSC. Initial awareness of the problem of accessibility on the road became increasingly important due to its significant effect on the deliveries, which is explicitly addressed in Paper V, and Paper VI. The intensity of the colors in the boxes shows the progress of the methodology and where the most effort has been focused during the project.

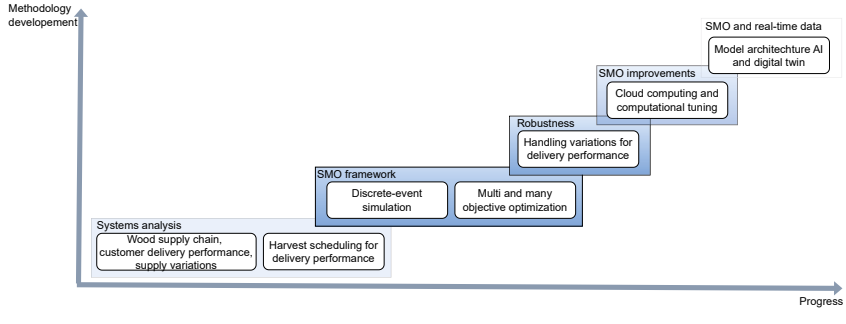


Figure 4.1. Iterative part of dissertation work.

In the four research questions (RQ1-RQ4), the role of SMO as a methodology to support decision-making in multiple objectives for enhanced wood supply delivery performance is addressed, which is the aim of this dissertation.

4.1 Paper I

The initial focus of this dissertation was to explore the impact of weather on delivery performance, particularly through its effects on road accessibility. This led to the question of how optimization could improve delivery performance when both road accessibility and customer demand are considered in the harvest scheduling problem. To do so, a simulation-optimization model was developed. In the DES, harvest operations are performed at each site according to the sequence determined by an optimized harvest schedule that captures backorders and lead time for each product. The harvest schedule, input into the DES, is based on an expected average weather scenario, which determines the periods when roads are accessible and the monthly customer demand. Hence, the effect of weather on landings was incorporated into the model, and a single-objective mixed-integer programming model was developed to schedule deliveries for even flows, considering demand and accessibility at the landings. The WSC was simulated in a DES model of the wood supply for a year in a region of harvesting sites and customer demand for five products.

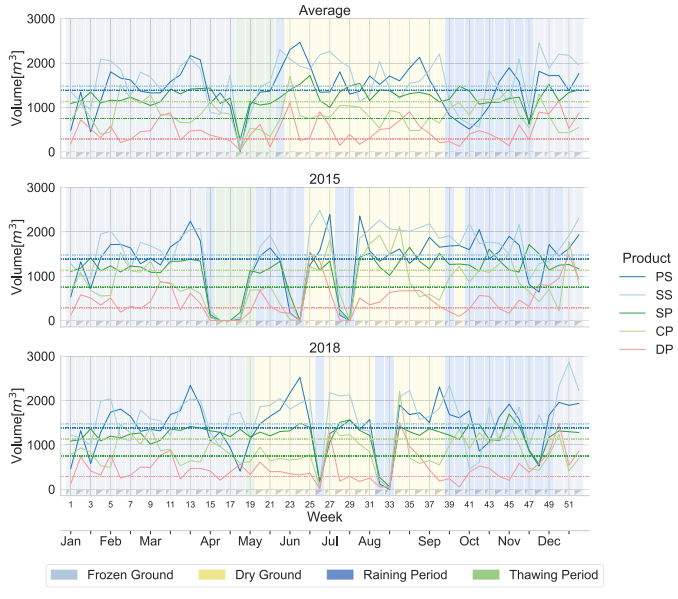
The bearing capacity of the road is described by the road classification system (Biometria, 2021) Table 4.1, and determines the accessibility to landings in the DES using the Boolean value. In the model, an average weather scenario based on weather data from Swedish Meteorological and Hydrological Institutes (SMHI) from 2015 to 2020 was used, i.e., a baseline scenario, in the optimization to calculate the harvest schedule. This average weather scenario can be regarded as a simpler decision rule for road accessibility.

Table 4.1. *Assessment of the accessibility of a roadside landing given its accessibility class and the weather condition, based on the classification by (Biometria, 2021), from Westlund et al. (2024).*

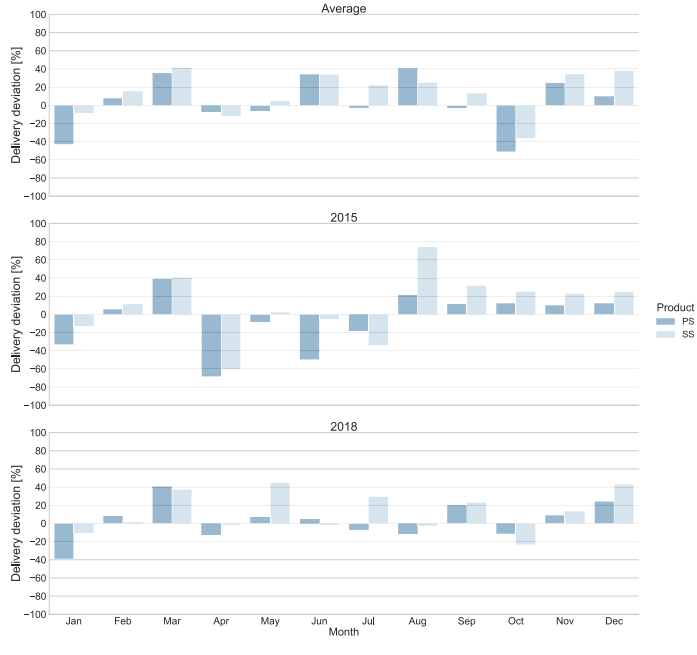
			Accessibility given weather condition		
Accessibility class	Definition	Frozen Ground	Dry Ground	Raining Period	Thawing Period
A (highest)	Accessible full year	True	True	True	True
B	Accessible full year except during thawing periods	True	True	True	False
C	Accessible full year except during thawing periods and continuous rain periods	True	True	False	False
D (lowest)	Accessible only on frozen ground	True	False	False	False

Two extreme weather scenarios were selected to examine the effects of varying weather conditions. 2015 had the highest deviation from the average scenario, and 2018 had the lowest deviation among the five datasets. The schedule for the baseline scenario was then used to simulate a realistic situation in which harvesting sites are pre-scheduled according to demand and a feasible (average) weather scenario, while acknowledging that actual weather conditions are likely to vary. Variations in weather were described by the different scenarios for 2015 and 2018. The results are shown in Figure 4.2.

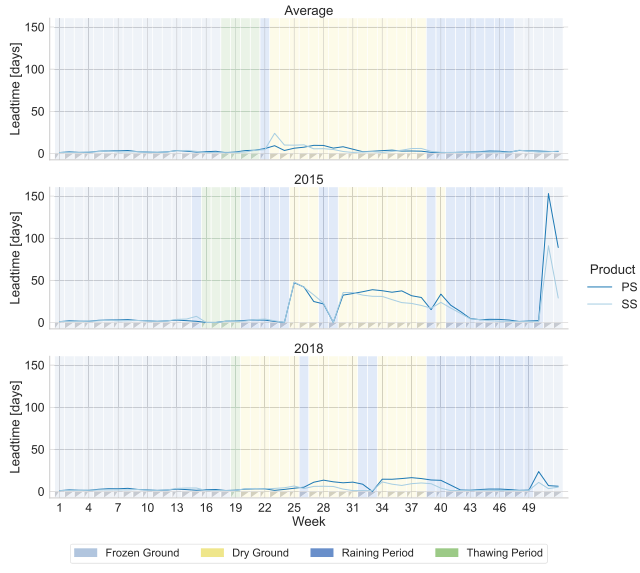
Figure 4.2a shows how deliveries vary compared to demand (dotted line) for different weather scenarios, where rainier periods reduce deliveries. This can be seen in the large drops in early and late summer in 2015, but also in 2018 in rainier periods, although conditions were the best of the five years.



(a) Total customer deliveries per month in the three simulated weather scenarios. January is affected by the lack of a warm-up period in the simulation run.



(b) Backorders per month in the three simulated weather scenarios. January is affected by the lack of a warm-up period in the simulation run.



(c) Lead times per month in the three simulated weather scenarios. January is affected by the lack of a warm-up period in the simulation run.

Figure 4.2. Assortment in the three figures, pine sawlogs (PS), spruce sawlogs (SS), spruce pulpwood (SP), conifer pulpwood (CP), and deciduous pulpwood (DP). All figures from Westlund et al. (2024).

In Figure 4.2b, the deviations in the monthly deliveries are shown, and in Figure 4.2c, the weekly lead time for the sawmills is shown.

The results show that variations in road accessibility, corresponding to what was expected in the scheduling (i.e., the average weather scenario), have a less negative impact on delivery performance. Delivery deviations and lead time increased for variations not expected in the scheduling. For 2015, compared to the baseline scenario, the lead time increased, particularly in wetter conditions, and remained behind for a while afterwards, as seen in Figure 4.2c. The same applies to delivery deviations, where the effects take time to repair. In particular, even in 2018, with good conditions, the average scheduled scenario is applicable most of the time. However, similar effects to those observed in 2015, when more rainy weather than expected developed, could also be seen in this year's lead time, which increased following a rainy period. These figures illustrate how delivery patterns are related to weather and road accessibility, resulting in fluctuations even with an optimized harvest schedule.

The contribution of this study lies in the introduction of a simulation-optimization framework for wood supply that captures the delivery performance outputs of a harvest scheduling optimization model, which are not easily represented in objective functions. The study was designed to capture how

road accessibility affected the performance of deliveries, where deliveries were scheduled according to demand and a feasible weather scenario based on historical data. Delivery performance, in the context of customer satisfaction, was assessed by measuring deviations from the monthly demand and the delivery time from harvest to customer. The knowledge contribution involves the optimization and simulation design to evaluate deliveries from a harvest schedule optimized for weather-dependent road accessibility. The results suggest that weather variations will have adverse effects on the performance of the WSC, raising the question of how to address road accessibility in scheduling and the handling of multiple delivery performance objectives.

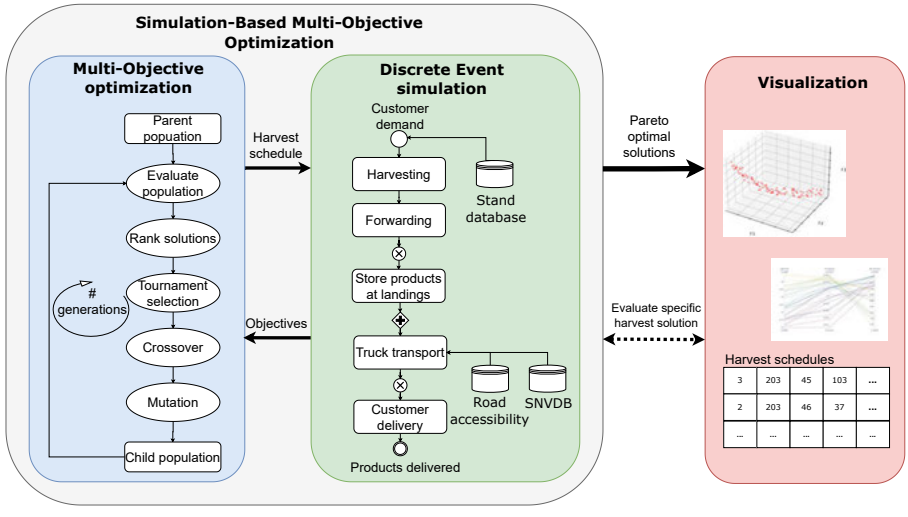
4.2 Paper II

In Paper II, the research area of SMO and its configurations is explored and developed. The delivery performance is formulated in the objectives, which can be conflicting and must be handled simultaneously. An extended lead time can improve delivery performance so that landings are filled with wood, making it easier for transport to find a load to deliver. However, this can result in a long lead time for wood in landings, where long lead times carry a risk of quality loss, and where reducing lead time is crucial to minimizing quality loss.

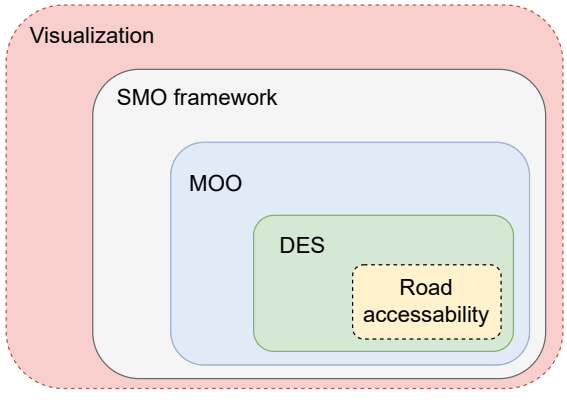
Three delivery performance objectives are proposed as a (common) supply chains baseline for an SMO framework with the objectives: service level, lead time, and throughput, thereby measuring productivity in the WSC. Service level is a standard measure in manufacturing supply chains, defined as the perceptual success in deliveries according to demand. The framework aims to present Pareto-optimal trade-off solutions for annual harvest scheduling as a decision support tool. A weather scenario determines road accessibility in the simulation, and accessibility to a landing is defined as a Boolean value.

The paper presents a framework comprising different components, as shown in Figure 4.3. As in paper I, the complexity of WSC is simulated using a DES model, providing objective function evaluations (fitness values). The DES model of wood supply was implemented in Facts Analyzer (Ng & Bernedixen, 2018), described in the conceptual model in Figure 4.3a, generally following the description in paper I. Facts Analyzer facilitates easier interaction with external software and provides a C++ programming interface, enabling programmatic customization of modeling within a code environment. The outputs for delivering the performance objectives can be captured, and the simulation can start after new inputs are provided. Hence, this aligns with the iterative approach SMO employs, incorporating multi-objective optimization into the runs.

The objective functions for the annual scheduling measures service level, lead time, and throughput were defined as in Equation (4.1)-Equation (4.3),



(a) Connections between the components in the framework, from Westlund et al. (2025).



(b) Structure of how the components in the framework build upon each other.

Figure 4.3. Conceptual model of the components in the SMO framework.

$$\text{maximize} f_1(\mathbf{x}) = \textit{service level} = \sum_{t \in T} \sum_{\in P} \frac{D_{pt} - WD_{pt}}{D_{pt}} \tag{4.1}$$

$$\text{minimize } f_2(\mathbf{x}) = \textit{lead time} = \sum_{p \in P} \frac{\text{variant process time}_p}{P} \tag{4.2}$$

$$\text{maximize} f_3(\mathbf{x}) = \textit{throughput} = \sum_{p \in P} \frac{\text{throughput}_p}{P} \tag{4.3}$$

, where $p \in P$ represent products, $T = \{1, ..., 12\}$ denotes the months, D_{pt} is the demanded volume of product p in time period t, and WD_{pt} is the delivered volume of product p in time period t.

Multi-objective optimization is developed based on the Python package pymoo (Blank & Deb, 2020), customized for this problem, and calling a DES model for fitness evaluation. Road accessibility is integrated in the DES, Figure 4.3b, which determines whether roads are accessible for transport, utilizing the average road accessibility scenario from paper I. The Pareto-optimal front is visualized in a dashboard prototype, built on the open-source Python package dash to visualize the results in a web application. A prototype for web visualization is presented, where the DES can be used to post-process the results.

NSGA-II (Deb & Jain, 2014), an established genetic algorithm used in several scheduling problems (Rahimi et al., 2022), was implemented for multi-objective optimization. The harvest scheduling problem is of the permutation type, where suitable operators are required to improve the solutions using an appropriate algorithm, combining the best solutions (parents) with improved solutions (children). As with many optimization problems, an initial solution that provides guidance can reduce the number of iterations and, consequently, the computational time. NSGA-II was initialized with a harvest schedule start solution, prioritizing the service level for the first population. To customize the NSGA-II operators, experiments were conducted to explore possible crossovers suitable for this permutation problem. Figure 4.4 shows how the sequence in the harvest schedules differs between the crossover operators. Customization of the operators forms an essential basis for SMO, which will be utilized in further work.

Three types of crossovers were evaluated, where the partially mapped crossover (PMX) (Goldberg & Lingle, 1985) and the order crossover (OX) were found to be suitable for the problem. The OX has a larger spread of solutions, but PMX was recognized to provide better convergence for service level. The results for the crossovers and the Pareto solution are shown in the two objectives, service level and lead time, Figure 4.5, also showing the single-objective solution from Paper I. The figure shows the convergence in the objectives and that the evaluated crossovers perform better than the single-objective approach in Paper I.

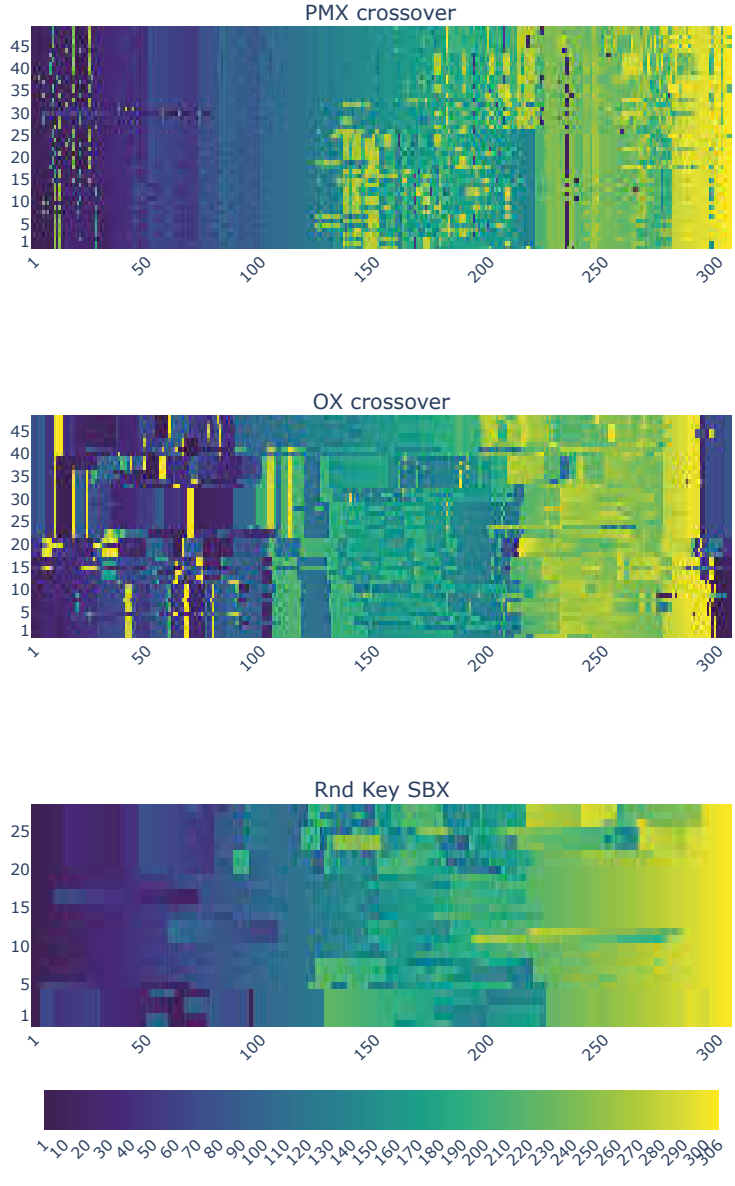


Figure 4.4. Heatmaps for the harvesting sequences from different crossovers, site IDs on the x-axis and solution number on the y-axis, sorted on service level ascending. The single objective solution, focusing on the service level, of the site ID sequence is used as a reference. From Westlund et al. (2025).

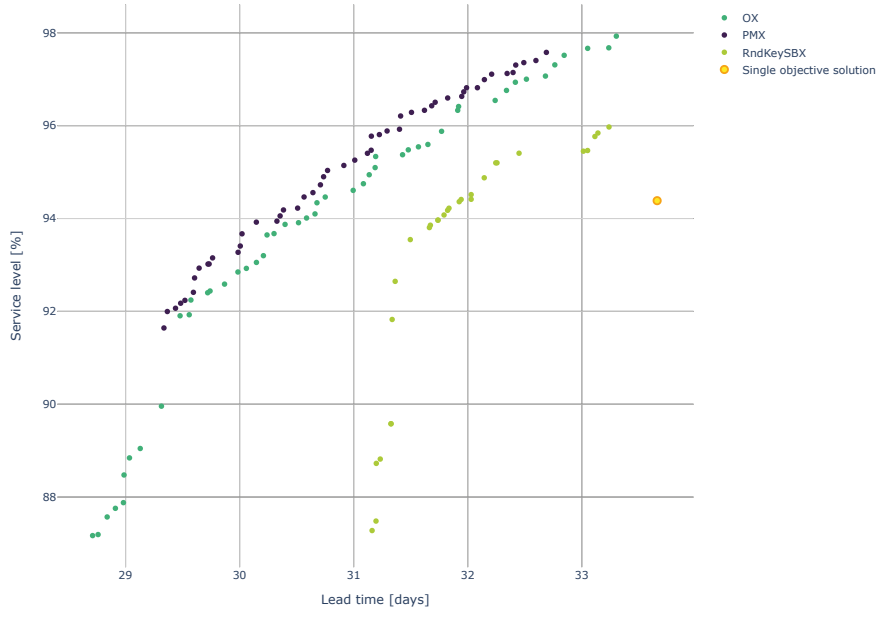
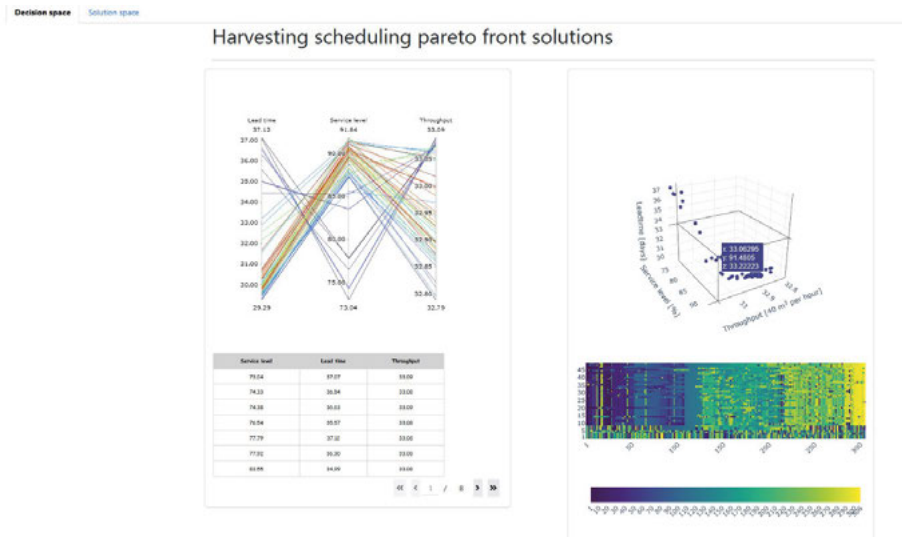


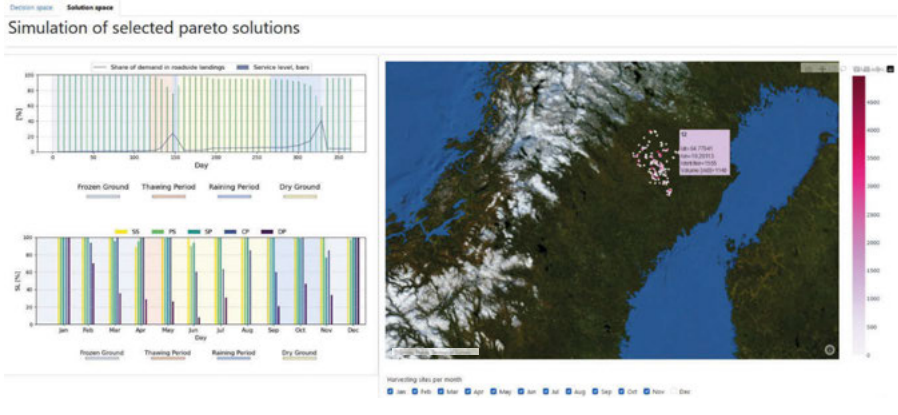
Figure 4.5. Service level and lead time [days] for partially mapped crossover, order crossover, and random key simulated binary crossover. The single objective solution is shown in orange, from Westlund et al. (2025).

Figure 4.6 illustrates how a dashboard prototype can be utilized to visualize the results and experiment with harvest solutions. The dashboard prototype is added as a layer on top of the SMO, adjustable for stakeholders, and is built using open-source Python libraries.

The main contribution of this paper is the introduction and development of an SMO framework that can handle multiple objectives, with an application to harvest scheduling, incorporating the impact of weather on road accessibility. The framework is flexible, allowing both inclusion of more or other objective functions and changes in the multi-objective algorithms. This is due to the framework concept, where components can be "disconnected," making them independent of the DES software or the multi-objective optimization algorithm, which can be customized according to the explicit problem formulation provided by the decision-maker.



(a) Tab one in dashboard prototype - selection of solution.



(b) Tab two in dashboard prototype - simulation of the solution in decision space ("tab1") with details from the simulation.

Figure 4.6. Dashboard example is a dash prototype for decision support and visualization of solutions, from Westlund et al. (2025).

4.3 Paper III

This paper explores how to incorporate robustness in deliveries into the SMO's objective functions, where a loss function is proposed influenced by the paper of Sanchez and Sanchez (2020). The aim is to integrate robustness in harvest scheduling optimization by addressing service level and throughput maximiza-

tion while minimizing lead time and monthly delivery deviations, which are measured as a loss function.

The expected loss function for a product is denoted $E[\iota] = \sigma_{D_i}^2 + (E[D_i] - \tau)^2$, where σ_{D_i} is the variance in monthly delivery deviations for the harvest solutions i. $E[D_i] - \tau$ is the average monthly delivery deviation for the same solution. This loss function penalizes deviations in variations between months and average deviations from monthly customer demand, aiming to achieve smoother deliveries throughout the months. Minimizing the loss function can entail a trade-off, where expected deviations from customer demand may be prioritized if they imply an improvement in one or more of the other objectives, such as lead time, or vice versa. The robustness objective was added to the SMO framework, and objectives from Paper II were computed to calculate Pareto-optimal harvest schedules in multiple objectives.

The results are shown in Figure 4.7, where the parallel plot shows that solutions with a low loss function and a high service level correspond to longer average lead times. Most solutions with the lowest loss values, the least monthly delivery variations, have the longest lead times, and the worst service level, between the average and worst-performing scenarios. However, there exist solutions with loss in the lower and mid-range, where service level is at its best and lead time is toward the lower range of days. Throughput is included in this analysis to examine the relations with productivity when incorporating robustness in deliveries. However, as was indicated in paper II, the productivity of the entire supply chain can be minimally influenced by harvest scheduling. This is also evident in this study. All solutions show the same throughput of approximately 33 truckloads per hour, with some solutions marginally better; however, this does not make any practical difference.

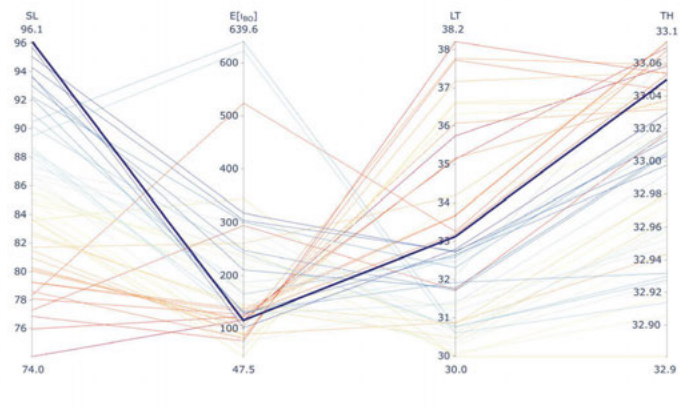
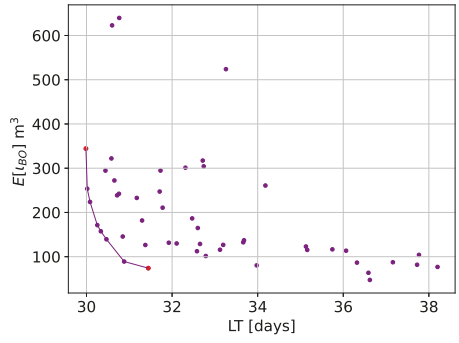
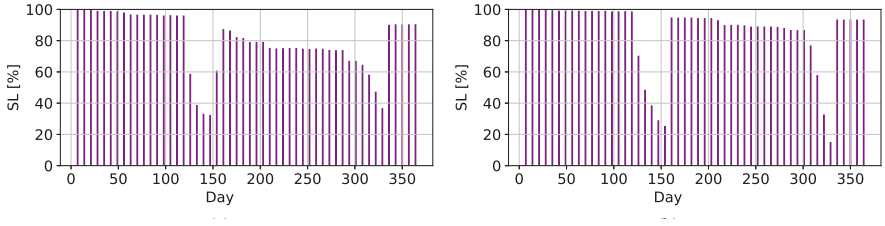


Figure 4.7. Parallel plot of the Pareto-optimal solutions. SL - service level, LT - lead time and TH - throughput, from Westlund and Ng (2024).

The DES can be used to post-simulate the harvest solutions to analyze the differences in objective values further. This was done for the most extreme Pareto-optimal solutions for loss and lead time, which were analyzed in the DES. Two Pareto-optimal solutions with the highest performance in terms of annual average lead time and monthly average loss, as opposed to the opposite, are highlighted in Figure 4.8a and simulated in the DES. The lead time is relatively short for both solutions, although there is a difference in the loss function. The results are shown in Figure 4.8b.



(a) Pareto-optimal solutions, lead time (LT) versus loss function.



(b) Service level (SL) for the highlighted solutions in (a). High loss to the left and low loss to the right.

Figure 4.8. Highlighted solutions from Figure 4.8a simulated in the DES where the difference in service level is shown in Figure 4.8b, figures from Westlund and Ng (2024).

In Figure 4.8b, it is clear that the variation in service level differs between solutions, where the solution with a high loss has relatively more variations. At the beginning of the year, when winter is expected and most roads are accessible, both solutions have delivered a high service level. However, in spring, during the thawing period, many landings become inaccessible, and road accessibility decreases due to natural causes. This can be seen in the figures, where the service level in both figures decreases after about 100 days. What differs between the scenarios is the recovery in service level, as shown in

the right figure for the solution with the lowest loss. Even if the service level drops, and the customer demand is not fulfilled during that time, the reduction in service level is lower for the solution with the lowest loss objective value.

The main contribution of this paper is the use of robust design. Although the form of the loss function may continue to evolve, the key contribution is the conceptual integration of the loss function to enhance robustness in planning. The SMO framework enables the inclusion of more objectives for decision-making, as in a real-world scenario. Expanding the framework by suggesting a loss function to manage robustness in deliveries contributes to more robust scheduling, ensuring smooth and even customer deliveries from month to month. The service level is an average annual measure; however, monthly fluctuations are accounted for by an objective function in the model. This paper also highlights the advantages of DES itself for experimentation, where solutions can be tested and where DES can provide more detailed insights into the impact of a schedule on the WSC.

4.4 Paper IV

A growing number of delivery performance objectives will increase the demands on the algorithms. As the solution space increases in solution density, it becomes more difficult for the algorithm to navigate in the heuristic search, where other algorithms are needed. Therefore, to prepare the framework for more objectives, alternatives to NSGA-II must be evaluated.

NSGA-II is primarily developed for up to three objectives, although it can be used for more than three. However, NSGA-II is not intended for many-objective problems (between four and 15 objectives) and is weaker in handling many objectives. There are a number of genetic algorithms suitable to handling many different objective problems. NSGA-III (Deb & Jain, 2014), is a descendant of NSGA-II offering an effective algorithm to handle many objectives. The primary difference from NSGA-II is the requirement for defined search directions to guide the algorithm in achieving spread and diversity during the search for solutions. To simplify, the search in the reference directions replaces the crowding distance in NSGA-II.

As outlined, the SMO framework is flexible in its components, such as the multi-objective optimization algorithm, allowing for the exploration of other algorithms. With more objectives or changes in the objectives, the DES must be updated to calculate the objectives in the simulation. Experiments were conducted for four objectives to analyze how and whether NSGA-III can replace NSGA-II in the SMO. Of course, there are applications where the number of objectives is much more than four. Still, with increasing objectives, the trade-off alternatives also increase in the decision-making process for the manager, although Pareto solutions can still be provided.

The model employs four objectives to test NSGA-II and NSGA-III on their cutting border, aiming to provide as many equal opportunities as possible. The objectives used were lead time, backlog, backlog loss (as presented in Paper III), and the coefficient of variation of backlogs for all products, denoted as CoV. In $CoV_{BL_{product}}$, the backlogs were weighted per product, $\omega_{product}$, in the total backlog and CoV for all products, because it can vary between products. Minimization of CoV was chosen to suppress the standard deviation between backlogs across different products in monthly deliveries, as this is not reflected in the loss function of either component. Hence, four objectives were optimized in this setting for comparison between NSGA-II and NSGA-III, product weighted: annual lead time, backlog, loss function for monthly deliveries, and the Cov of monthly backlogs. The DES was modified to handle the four objectives in the simulation, and the multi-objective optimization was coded to be flexible concerning which algorithm to use in the SMO.

NSGA-II and III from the pymoo (Python package) (Blank & Deb, 2020) were used and customized for the problem. Both algorithms require setting a population size and the number of generations to follow the same process in the comparison, as shown in Figure 3.4. The elitist operator in NSGA-III utilizes reference directions for ranking and selecting solutions to preserve, rather than using crowding distance as in NSGA-II. NSGA-III requires predefined reference points that are evenly and well spread on the unit simplex. The number of reference points in NSGA-III is related to the population size in NSGA-III, as discussed in Section 3.2.4, where increasing the number of reference directions also increases the population size. This is also a bottleneck with reference-based search methods, where the population size should be at least as large as the number of reference points.

Both NSGA-II and NSGA-III, along with their respective setups, were implemented on an on-demand Azure Virtual Machine with 16 CPUs, which is a reasonably low number, but more than what is available on an ordinary laptop computer. This will reduce the computational time with the adopted or available CPUs.

The NSGA-II was run for a population of 100 and 100 generations, while the DES was run for five replications. The SMO's runtime was 22 hours, utilizing 12 of the 16 cores in the parallelization. The paper provides a more detailed explanation of the parallelization procedure. In particular, the runtime was reduced from a week to one day for an experiment involving 10,000 SMO runs with 5 DES replications. The NSGA-III reference directions were set to 84 points from six partitions, using the "Das-Dennis" formula (see Section 3.2.4) to approximate the 100 used in NSGA-II. To achieve an equal comparison, the prerequisites for the algorithms should be as similar as possible.

The Pareto solutions are shown in the pairwise plot in Figure 4.9, with NSGA-III colored purple and NSGA-II in green. The loss for backlogs is scaled with a log function for readability. NSGA-III found 26 solutions, and NSGA-II 100 solutions. Despite the fever solutions in NSGA-III, the spread is

more diverse due to the given reference directions, and the front is well covered. NSGA-III outperforms NSGA-II, as shown in the plot. For the backlog versus loss function, the solutions converge, as expected.

Figure 4.9. NSGA-III (purple) and NSGA-II (green) solutions for pairwise objectives. Marked solutions are for a follow-up in a dashboard visualization. From Paper IV.

When the actual front or optimal values are unknown, it is difficult to measure performance. However, hypervolume (Fonseca et al., 2006) can be used for an equitable comparison. Hypervolume is a measure of the coverage of a fictive volume spanned by the Pareto front solutions according to a reference point applied for the compared algorithms. The progress of the hypervolume measure for generations is shown in Figure 4.10, where NSGA-III has a higher value and therefore a better front coverage, becoming stable faster than NSGA-II.

Finally, two of the best solutions in both fronts (purple and green stars in Figure 4.9) for backlog and lead time were chosen and simulated in the DES to

capture more details regarding the differences. The backlog is shown on the right y-axis, and the back order, i.e., the difference in backlogs, is shown on the left y-axis. The results of the simulations are shown in Figure 4.11, where it can be seen that, in general, the backlog for NSGA-III is lower than for NSGA-II, and the variations, as indicated by the number and size of the bars, are lower in NSGA-III. The backlog is bigger in the NSGA-II solution at the end of the year (dotted lines). In both cases, an increasing variation in backlog and backorders (delivery failed in a specific month) can be observed in the spring and the beginning of summer, from April to June. The thawing period starts in April and is likely to affect accessibility to landings during this time, causing disturbances and decreasing delivery performance.

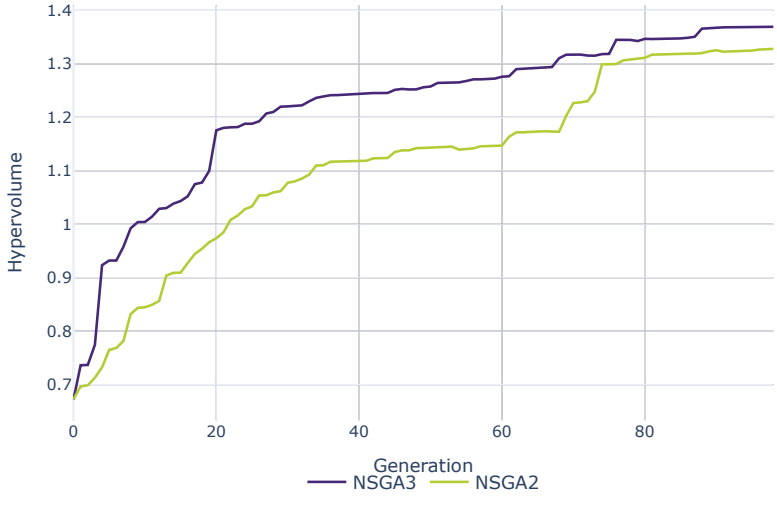
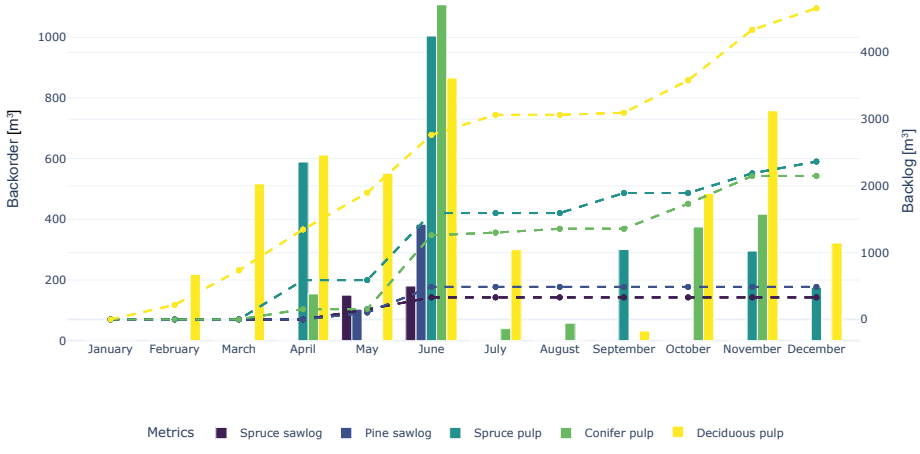
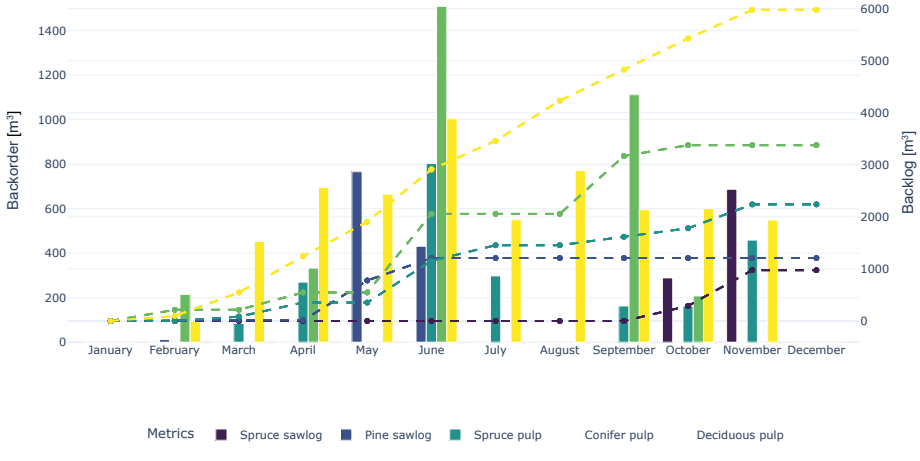


Figure 4.10. Hyper volume comparison of NSGA-III and NSGA-II, from Paper IV.

The contribution of this paper lies in the application of NSGA-III to the harvest scheduling problem, which can be useful as the number of objectives increases within the SMO. The use of parallel computations enables a more efficient calculation process, improving computation time, while the cloud computation environment brings the methodology closer to a real-world scheduling environment. For a real-world problem, computation time is critical. This setup, utilizing Python open-source packages in conjunction with an online-demand computing environment, applies to any specific software environment.



(a) Simulated NSGA-III solution marked in Figure 4.9.



(b) Simulated NSGA-II solution marked in Figure 4.9.

Figure 4.11. Back orders are shown as bars, and backlogs as dotted lines. All figures from Paper IV.

4.5 Paper V

In Paper V, the robustness in harvest scheduling is the focus and approached from the perspective of deep uncertainty (Lempert et al., 2006), using two met-

rics to evaluate alternative candidate harvest scheduling solutions for robustness. The metric evaluates how robust a harvest schedule is under varying weather scenarios, measuring the extent to which a solution can maintain the targeted delivery performance objectives. Robustness metrics are an alternative when probabilities for road accessibility scenarios are lacking. An Azure Virtual Machine with 12 cores, combined with parallelization of the calls to the SMO executable, was used to reduce the optimization time to less than two days.

The objectives in the SMO are divided into assortment groups, sawlogs, and pulpwood for two time periods: week 1-13 (January - March) and week 14-52 (April - December), where the choice of periods is flexible in the model. This is to split the scheduling period to enable decision-making and handle trade-offs from both short and longer perspectives, while minimizing delivery variations for both periods. The trade-offs can also differ over the planning horizon; for example, a situation may prioritize short lead times before an expected thawing period to reduce the risk of getting wood trapped at inaccessible landings.

Lead time, $\mathrm{LT}_{\mathrm{sawn}}(x,A)$ and $\mathrm{LT}_{\mathrm{pulp}}(x,A)$, is defined as the average number of days between harvest and delivery to industry for harvest schedule x and accessibility scenario A. Backlog, $\mathrm{BL}^{1\text{–}13}_{\mathrm{sawn}}(x,A)$, $\mathrm{BL}^{14\text{–}52}_{\mathrm{sawn}}(x,A)$, $\mathrm{BL}^{1\text{–}13}_{\mathrm{pulp}}(x,A)$, and $\mathrm{BL}^{14\text{–}52}_{\mathrm{pulp}}(x,A)$, is defined for each month as the unfulfilled demand in cubic meters at the end of a period, and the maximum backlog obtained during these two periods. The objective functions are:

$$\begin{aligned} &\text{minimize} && \mathrm{BL}^{1\text{–}13}_{\mathrm{sawn}}(x,A),\ \mathrm{BL}^{14\text{–}52}_{\mathrm{sawn}}(x,A),\ \mathrm{BL}^{1\text{–}13}_{\mathrm{pulp}}(x,A),\ \mathrm{BL}^{14\text{–}52}_{\mathrm{pulp}}(x,A) \\ &\text{minimize} && \mathrm{LT}_{\mathrm{sawn}}(x,A),\ \mathrm{LT}_{\mathrm{pulp}}(x,A) \\ &\text{subject to} && x \quad \text{a harvest schedule,} \\ & && \quad \text{i.e., any permutation of site indices } \{1,\ldots,n\} \end{aligned} \tag{4.4}$$

The SMO framework calculates harvest schedules for an average weather scenario, where Pareto-optimal solutions are evaluated for varying weather scenarios. Each of the 100 Pareto solutions calculated in the SMO was analyzed for 1000 samples of feasible weather scenarios, omitting obvious scenarios such as frozen ground in summer. Each of the 100 Pareto-optimal harvest schedules was simulated in the DES for the 1000 road accessibility scenarios to evaluate the robustness to variations in road accessibility and the corresponding delivery performance in the objectives. Despite Pareto optimality, the objectives of Pareto-optimal harvest solutions were expected to deviate from the original values in the average weather scenario. The robustness of a solution is determined both by the degree of deviation, compared to the best solution in that objective, and by how many weather scenarios meet the defined thresholds for the objectives.

Two robustness metrics were applied for robustness evaluation, *maximum regret* (MR) and *domain criterion* (DC), as strategies to minimize worst-case scenarios. In *maximum regret*, the metric compares the best objective values

obtained in any harvest schedule x and scenario A, to which all other schedules and scenarios are compared. *Maximum regret* is defined as:

$$\mathrm{MR}(x) = \max_{\text{all scenarios } A} |f(x,A) - \underset{\text{all schedules x'}}{\text{best}} f(x',A)| \tag{4.5}$$

where f is any of the objectives. Regret is defined as the difference in each objective, where maximum regret is the maximal difference over all accessibility scenarios. Hence, a low maximum regret value implies a more robust harvest schedule.

The *domain criterion* metric indicates the proportion of accessibility scenarios that meet a minimum performance threshold, as defined in the objectives. These thresholds are typically set by the decision-maker. The threshold defines what is acceptable, e.g., how long a lead time is acceptable for a product. The *domain* describes the share of that *domain* a solution covers, where higher values are preferred, indicating robustness. The definition is:

$$\mathrm{DC}(\mathbf{x}) = \frac{1}{\text{no. of scenarios}} \sum_{\text{all scenarios } s} g(\mathbf{x}) \tag{4.6}$$

where $g(\mathbf{x})$ is an indicator to represent 1 if the threshold is satisfied for the corresponding objective function and scenario, and otherwise $g(\mathbf{x}) = 0$.

To demonstrate the variations in the solutions, the yellow and blue lines corresponding to two solutions of harvest schedules (1000 lines each) are shown, Figure 4.12.

The best performance in each objective function and scenario was identified for maximum regret, named the *zero regret*. Applying Equation (4.5) for each solution and objective, the differences between the objectives and zero regret for all scenarios were calculated to get the maximum regret of a solution and its respective objective. A close-to-zero maximum regret value represents better robustness in that solution. To determine which solutions have the best maximum regret or robustness, each solution's maximum regret values are compared with the objective values. This is shown in Figure 4.13a.

For the domain criterion, thresholds must be set for acceptable values of the objective functions. In this analysis, the least acceptable threshold values are set for illustrative purposes, see Table 4.2. A harvest schedule solution is considered robust if the objective function value is, at a maximum, as high as the threshold value, e.g., the lead time for sawlogs in this example should be less than 35 days. Aligning the domain criterion score from Equation (4.6) and calculating the share of the road accessibility scenarios covered for a solution gives the robustness score, where the higher the score, the better "coverage" for road accessibility scenarios. This is shown in Figure 4.13b.

Both metrics in Figure 4.13 can be used complementarily in the decision-making as a guide to more robust harvest scheduling solutions when deciding which harvest schedules are preferable. The interactive visualization, where the parallel coordinates (Figure 4.12 and Figure 4.13) are made interactive,

Table 4.2. *The least acceptable performances (thresholds) in each objective function. From paper V.*

Objectives	Thresholds
Max. backlog weeks 1-13, sawn	< 2000
Max. backlog weeks 1-13, pulp	< 2000
Max. backlog weeks 14-52, sawn	< 20000
Max. backlog weeks 14-52, pulp	< 15000
Avg. lead time, sawn	< 35
Avg. lead time, pulp	< 35

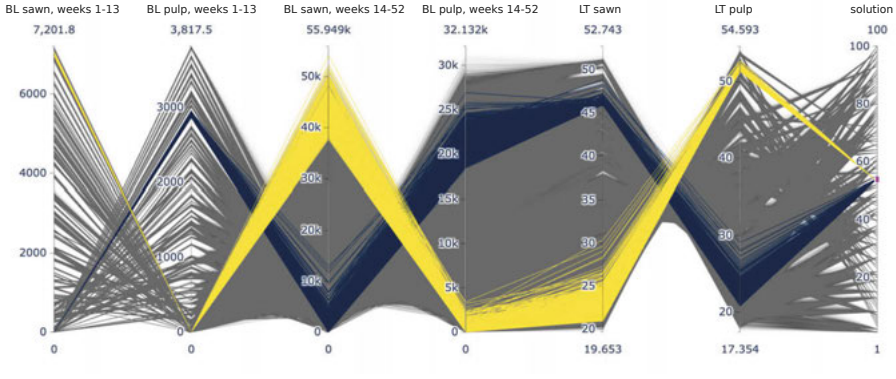
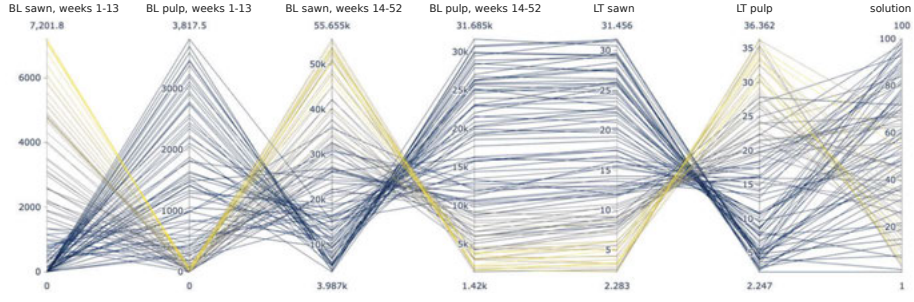


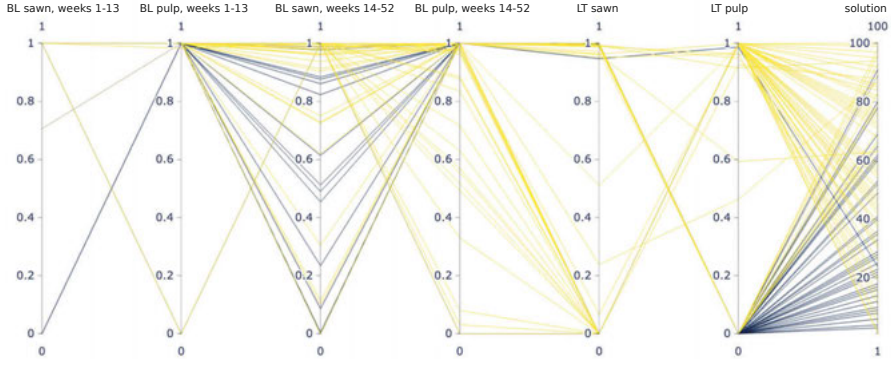
Figure 4.12. Objective function values obtained for the 100 non-dominated harvest schedules when re-evaluated in the 1000 accessibility scenarios. Each poly-line corresponds to one harvest schedule evaluated in one scenario. The 1000 re-evaluations of two harvest schedules are highlighted in yellow and blue, respectively, to demonstrate the ranges in objective function values. From Paper V.

allows for filtering solutions by "click-and-drag". This is particularly useful for experimentation and analysis of solutions. Solutions can be filtered for comparisons to identify more robust solutions, and adding objective thresholds for all or each objective in the decision-making (of trade-offs).

The paper's contribution lies in the methodology used to identify harvest scheduling solutions that are more robust to varying road accessibility scenarios and less sensitive to weather variations. Without accurate road accessibility probability statistics, the two robustness metrics can be used to evaluate which harvest schedules are preferable to others. The visualization supports analyzing the objectives and trade-offs of the schedules for the maximum regret and domain criteria scores. This can guide the decision-making to improve delivery performance in the WSC.



(a) Maximum regret scores for the 100 non-dominated harvest schedules. The lower the score, the higher the robustness. Each poly-line corresponds to one harvest schedule.



(b) Domain criteria scores for the 100 non-dominated harvest schedules. The higher the score (number of scenarios), the higher the robustness since the more scenarios meet the acceptable threshold. Each polyline corresponds to one harvest schedule.

Figure 4.13. All figures from Paper V.

4.6 Paper VI

This paper proposes an architecture, extending the SMO framework with DT-AI to transfer the predictive model to a prescriptive state, enabling data-driven decision-making. It refers to the use of DT and AI applied to the SMO framework to adjust scheduling for uncertain supply and road accessibility using real-time data, and finally, in a real-time environment. The proposed DT-AI framework is an extension and improvement of the original SMO framework, utilizing RL, an AI method, to adjust the long-term operational harvest schedule in response to supply and accessibility uncertainties, in combination with a DT for real-time data updates. The RL agent is trained to dispatch trucks; specifically, it determines how many trucks should be utilized and which truck should transport from a given landing to a specific customer, taking into account current landing volumes and road accessibility. The improvement involves employing an objective to minimize transportation and reduce CO_2 emissions for deliveries when multiple customers are in the same product category and for non-designated harvest sites.

The extension involves using reinforcement learning to train the SMO framework in dispatching transports from landings to adhere to a chosen harvest schedule. The dispatching should adjust the transportation to varying road accessibility and variations in product quality volumes at landings, ensuring adherence to the original schedule. A developed AI model (Andersson, 2025), based on the current weather forecast, is used to predict road accessibility for the next five days, utilizing the Isolation Forest algorithm (Liu et al., 2008) to classify roads as accessible or inaccessible.

The RL algorithm is first trained offline in an initial stage, using weather and accessibility scenarios, to perform a rough first training of the decision-making agent. This helps make the more data-intensive online training phase more efficient, allowing the agent to focus more on fine-tuning and adaptation rather than learning everything from scratch. In the DT, relevant real-time data on the current landing status of product volumes, the number of available trucks, and momentary delivery performance are collected from the supply chain, along with the weather forecast. Hence, the DT-AI framework consists of three components shown in Figure 4.14: the SMO framework and adjusted objectives (CO_2), the RL agent for the dispatching of trucks to adapt to the scheduling, and finally, transferring from an offline training environment to an online scenario.

The paper's contribution is the proposed DT-AI architecture, extending the SMO framework, aiming to develop a prescriptive data-driven decision-making model. The DT-AI framework can be applied to a real-world scenario by collecting relevant data, such as weather forecasts and current landing statuses, to support the decision-maker in determining the actions to take based on likely future outcomes. The DT-AI framework utilizes the original harvest schedule, thereby maximizing the performance of the delivery with respect to the objectives, minimizing CO_2 emissions (or the distance of transport),

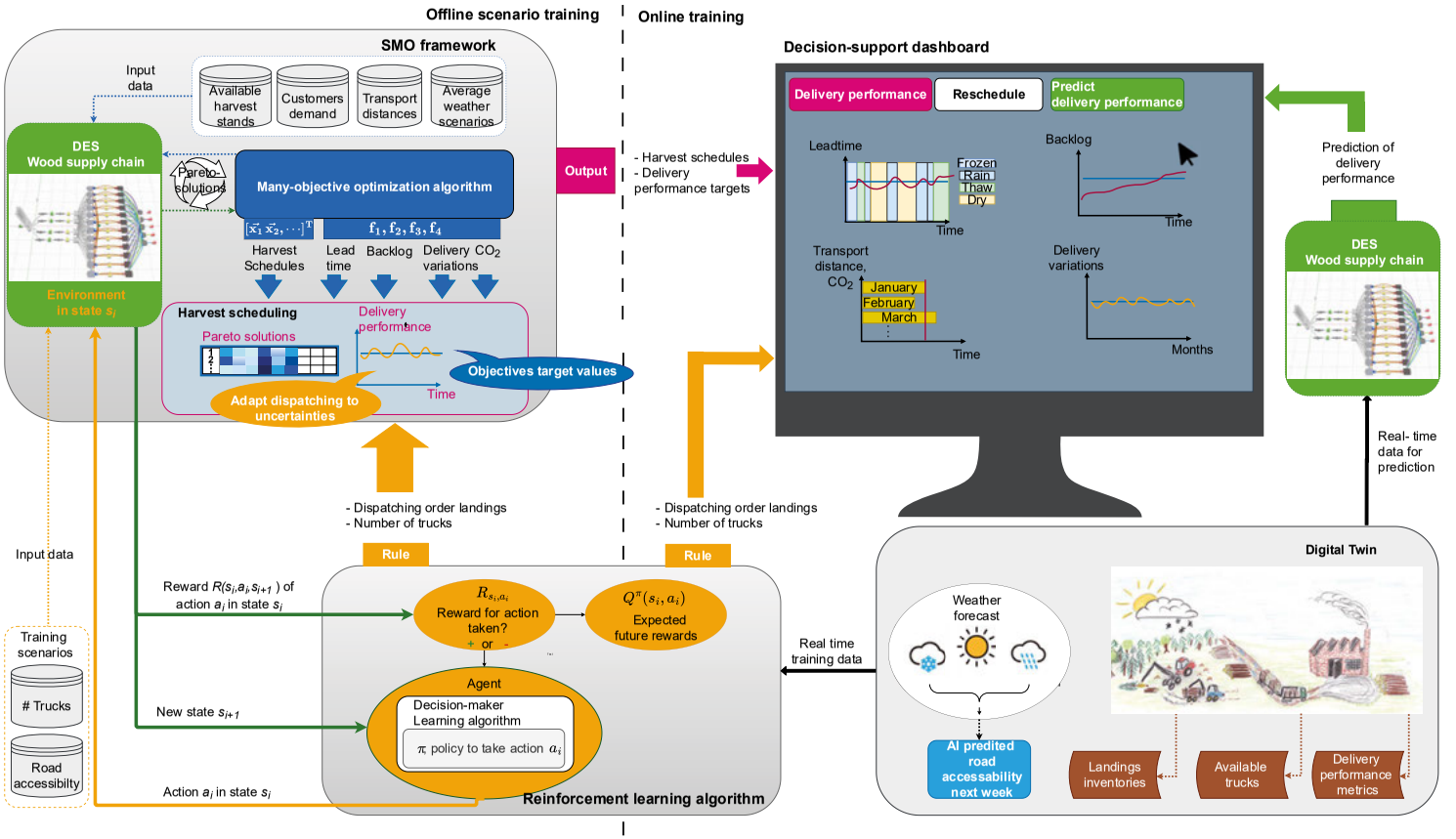


Figure 4.14. Conceptual model of the DT-AI framework. To the left, offline long-term operative harvest schedules optimized for delivery performance of CO_2 reduction, minimizing delivery variations, backlog and lead time for products. The RL model is trained to adjust the transport dispatching for varying weather scenarios. To the right, the RL is fine-tuned online using DT data of landing variations and current delivery performance, while predicting future road accessibility based on weather forecasts. Figure from Westlund and Ng (2025).

delivery variations, and backlogs. Adjustments are made in the number of trucks and the dispatching from harvest sites to customers, the goal being to adhere to the schedule to maximize the delivery performance.

5. Conclusions

This chapter concludes this thesis work by first summarizing the answers to the research questions and then the contributions to new knowledge resulting from the research outcomes.

5.1 Summary of the answers to the four RQs

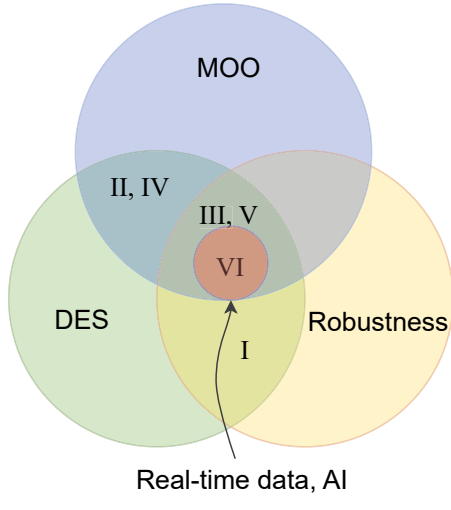


Figure 5.1. Relations between research areas and publications in this dissertation.

This thesis aimed to explore and develop a methodology for applying SMO to support decision-making in the WSC across multiple objectives. The focus was on expanding knowledge in SMO and its application in WSC. To achieve this goal, four relevant research questions (RQ1–RQ4) were formulated and addressed while iteratively developing an SMO framework. This framework embraces three key research areas, namely DES, MOO and robustness, as outlined in Figure 5.1 and linked to the papers discussed in Chapter 4. Real-time data and AI are added, where the SMO framework is the basis for this extension.

The response to the first research question, RQ1, is the development of the SMO framework, which integrates simulation and multi-objective optimization for the WSC. The framework was improved iteratively throughout the research and is based on a DES model of the supply chain combined with meta-heuristic optimization using genetic algorithms. The objective functions in the SMO can be modified depending on the problem configuration. Uncertainty in scheduling, due to weather-related impacts on transportation, is incorporated into the DES model. The SMO framework serves as a foundation for the methodology, which was adapted and extended to address the remaining research questions. The use of a baseline scenario for weather is a simpler decision rule, but the methodology can be adapted to other weather scenarios (RQ2).

Two key areas were identified in addressing RQ2 and RQ3: deviations in deliveries (supply that deviates from demand) and the accessibility of landings for transportation. Two approaches were applied to tackle these issues. To handle supply –demand mismatches, an objective function was added to the SMO (as part of RQ1) to minimize annual delivery backlogs. A loss function was also introduced to further improve the robustness of the delivery, promoting an even distribution of deliveries throughout the year and preventing end-of-year concentration. Based on averages and standard deviations, the loss function aims to smooth out the delivery variations between months. As already established in RQ1, the stochasticity of the road bearing capacity due to varying weather conditions was represented as Boolean values for each landing and scenario in the DES model. These scenarios can be replaced or extended, enabling robustness testing in different weather conditions and road accessibility conditions. The DES model supports both the SMO framework and detailed post-processing, such as comparing monthly delivery deviations, as shown in Paper III, Section 4.3

To handle variations in road accessibility, deep uncertainty was applied as another strategy using *zero regret* and *domain criterion* metrics to evaluate robustness across a wide range of weather or road scenarios. These metrics complement each other in guiding decisions by highlighting trade-offs and priorities and helping identify suitable harvest schedules. The deep uncertainty approach encourages decision-makers to participate in experimenting with scenarios and thresholds, thereby supporting the selection of preferred solutions based on informed trade-offs.

RQ4 is addressed in the extension of the SMO framework, adding a DT-AI for real-time data. As previously described, real-time data exist but are currently unavailable for research. The architecture design of a DT-AI presents how to address a limited amount of real-time data on current landings and road accessibility. However, such a project is currently being initiated to implement the proposed framework.

The SMO framework is flexible and can incorporate additional or alternative objective functions and multi-objective algorithms. Its design allows components to be disconnected or replaced, making the framework independent of

specific DES software, multi-objective optimization algorithms, or AI model extensions, thus partially addressing RQ4. The framework can be tailored to specific problem formulations, with components adaptable to various simulation tools or supply chain contexts, as long as objectives can be computed from a given harvest schedule. There are no software constraints for the multi-objective optimization algorithm, web visualization, or parallelized computations, as all components rely on Python open-source libraries. The same flexibility applies to computational resources when the framework runs on a standard laptop but can be scaled using on-demand computing. The overarching goal is to make the framework as accessible as possible, with open-source platforms playing a central role in that aim.

5.2 Contributions to knowledge

- **Contribution 1:** The proposed SMO framework provides a quantitative contribution by supporting decision-making for wood supply delivery performance across multiple objectives. It explicitly models how transportation is influenced by landing accessibility, which in turn is dependent on weather conditions.

- **Contribution 2:** The robustness of the SMO methodology for wood supply scheduling is enhanced by incorporating delivery variations into the SMO framework. This is achieved by introducing objective functions that mitigate fluctuations in delivery performance.

- **Contribution 3:** The framework addresses data unavailability or inaccuracy regarding road accessibility by modeling accessibility in the DES and SMO under various feasible weather scenarios. This represents a methodological contribution to address the effects of weather when real-time accessibility data are unavailable or when historical data do not accurately reflect current conditions.

- **Contribution 4:** A method to adapt the SMO to many objectives is proposed to provide flexibility for incorporating additional objectives.

- **Contribution 5:** The use of post-evaluation metrics for assessing robustness of weather-dependent road accessibility in the Pareto-optimal solutions. The nature of the contribution, qualitative or quantitative, depends on how decision-makers apply these metrics in practice.

- **Contribution 6:** A final contribution demonstrates how real-time data can complement the SMO framework by integrating a DT and AI methods. This

enables the framework to adapt to data-driven, prescriptive decision-making using current operational and environmental data.

6. Discussions and future work

In this dissertation, SMO was introduced, explored, and developed as a methodology to optimize multiple delivery performance objectives for the WSC, while accounting for uncertainty, particularly in road accessibility. There are various meta-heuristic methods for multi-objective optimization, but genetic algorithms are particularly effective due to their ability to explore diverse trade-offs simultaneously through population-based search. Genetic algorithms are computationally demanding, a known limitation (Branke et al., 2008). An Azure virtual machine was tested to speed up the calculation, providing on-demand computer power, and a smaller machine (16 CPUs) was used. This setup, along with the utilization of programmatic parallelization, demonstrates the potential to implement the SMO framework for practitioners through effective programmatic implementation and calculations, but more advanced parallel computing platforms to support more efficient SMO are worth further research.

Given the formulation of RQ4, it was intended to address how real-time input data updates can improve WSC scheduling, given that the knowledge of real-time data was established when formulating the research question. During the research, it became clear that real-time data were either unavailable or inaccessible, despite initial expectations based on the assumption that such data would be readily available in an advanced industrial context. The reality of the situation has shown that, even if forest companies collect many types of real-time data along the supply chain, the availability is restricted and fragmented, dependent on stakeholders and their internal data systems. Although this became clear, suggestions for future research are addressed concerning how real-time data can improve stakeholder decision support. In the future, it is expected that there will be a need to fully utilize AI in combination with a DT to provide effective operational decision support to forest decision-makers.

Road accessibility can vary stochastically. It is a key factor in delivery performance and was identified early in the project to have a significant impact on deliveries. Accurate data on road accessibility for each harvest site and time are difficult to predict, as they depend on the prevailing weather. Forest managers' knowledge and awareness of expected road accessibility scenarios are a primary source in the scheduling, as there are no exact systems to predict future bearing capacity. This might work well for an average weather scenario. Current weather situations, particularly expected future situations, will differ from what is considered as "normal," where unexpected inaccessibility disrupts the scheduling process. Jönsson and Lagergren (2017) forecast seasons for the operative planning of forest management using a soil model

and retrospective data from 1981- 2010. Climate changes will also affect accessibility (Daniel et al., 2018; Kellomäki et al., 2010; Lehtonen et al., 2019), with shorter frozen periods and increased precipitation putting pressure on robust scheduling. Real-time data can be part of the solution, supporting prescriptive analysis by allowing dynamic, up-to-date simulations combined with AI for decision-making. Access to accurate, real-time road accessibility predictions (Väätäinen et al., 2025) based on weather forecasts can significantly improve scheduling, making it more responsive to reducing road damage, lowering transportation costs and CO_2 emissions, and improving delivery performance in meeting delivery quotas for target customers. Having access to real-time data on product volumes on the landing reduces supply uncertainty and improves scheduling. Using updated and current data integrated into the simulation and optimization models allows for future predictions.

Data analytics involves processing (real-time) data to support decision-making by optimizing systems to improve and predict performance. When planning in an operational environment, data on the current status are used for predictions. Supply chain planning and scheduling are primarily based on historical data in simulation optimization modeling, which is mainly focused on descriptive and predictive analytics. In their paper on operational forest planning, Malladi and Sowlati (2017) concludes that advanced data analytics could be essential in transport planning for just-in-time production and vendor-managed inventory. Palander et al. (2024) discusse the importance of digitalization and data availability as key enablers of data-driven dynamic optimization for wood supply and effective system management. Real-time data enable the transition from diagnostic analytics and predictive analytics, ultimately to prescriptive analytics.

Based on the results discussed, it is suggested that future research should focus on integrating real-time data, such as DTs of the supply chain, into the SMO framework to adjust for uncertainties and respond to environmental changes. AI methods, such as RL, can adapt the dispatching of trucks to pre-optimized schedules, ensuring adherence to the schedule while accounting for uncertainties in landings and transportation requirements. In the first stage, the DT should be limited to relevant data for the AI model, with the least effort required to start using real-time data for informed decision-making.

The structure of the SMO allows for flexible objective definitions, provided that relevant input data is available. Alternative or additional sustainability objectives, accept from transport distance, can be integrated to assess trade-offs related to environmental, ecological, or social indicators associated with harvest scheduling, e.g., metrics for regional environmental values. It would be interesting to further develop the SMO, integrating sustainability metrics suggested and provided by domain experts to visualize strict monetary trade-offs against sustainability gains, or analyzing multiple sustainability objectives.

Sammanfattning

Virkesprodukter från skogen är en viktig komponent i en biobaserad ekonomi. Virkesråvara är en resurs som måste utnyttjas effektivt när den väl är avverkad, och möta kundernas leveranskrav. Ur ett kundperspektiv bör virkesleveranser, från skog till industri, ske i rätt tid, vara av rätt kvalitet och rätt kvantitet, oavsett vilka störningar som uppstår i försörjningskedjan. Leveransprecision sammanfattar dessa samtidiga och lika viktiga leveransmål i virkesförsörjningen.

Avverkningstidpunkten avgör när virket blir tillgängligt för transport och både avverkning och leverans måste stämma överens med kundens årliga och månatliga efterfrågan. En operativ långsiktig avverkningsplanering är avgörande för att uppnå leveransmålen. Avverkningsplaneringen bör också kunna möta flera samtidiga mål, t.ex. så korta leveranstider som möjligt för att säkerställa att råvarans kvalitet bibehålls och samtidigt leverera i tid för en eller flera produkter.

Samtidigt som planeringen bör klara fler leveransmål, påverkar osäkerheter såsom väderförhållanden och produktutfall möjligheten att leverera enligt plan. Även med en noggrann avverkningsplanering kvarstår väderrelaterad vägtillgänglighet som en kritisk framgångsfaktor för att uppnå leveransprecision. Vägarnas framkomlighet vid transporttillfället, efter avverkning, är avgörande för korta leveranstider och för att kunna leverera enligt planen. Avverkningsplaneringen bör helst erbjuda flera planeringsalternativ med hög leveransprecision för så många och samtidiga leveransmål som möjligt, samtidigt som de är robusta mot osäkerheter.

Den här forskningen introducerar en metodik för avverkningsplanering baserad på flermålsoptimering, sammanfattad i ett ramverk för simuleringsbaserad flermålsoptimering. Metodiken kombinerar metaheuristisk flermålsoptimering med diskret händelsesimulering för att ta fram avverkningsplaner som svarar mot flera samtidiga leveransmål. Genom diskret händelsesimulering kan den komplexa virkesförsörjningskedjan och dess leveranser modelleras utifrån en avverkningsplanering. Simuleringen möjliggör också integration av vägars framkomlighet, som beror av väder, och påverkar möjligheten till transporter från virkesavlägg till kund. Ramverket är anpassat till avverkningsplaneringsproblemet och utvärderas med olika målfunktioner som representerar olika och samtidiga leveransmål. Antalet leveransmål kan variera beroende på en beslutsfattares preferenser. De vanligaste leveransmålen för de flesta försörjningskedjor är ledtid och leveranssäkerhet för en eller fler produkter, vilka ingår som mål i optimeringen. En beräkningsmetod som är anpassad för att hitta lösningar för fler än tre – fyra leveransmål i avverkningsplaneringen föreslås också.

Flermålsoptimeringen presenterar fler möjliga avverkningsplaner som svarar mot de olika leveransmålen. Vid fler och samtidiga leveransmål måste en avvägning och prioritering mellan målen göras för att bestämma vilken avverkningsplan som passar för situationen. Det är en beslutsfattare, med kännedom om vilka mål som är prioriterade inom virkesförsörjningen, som kan avgöra vilken eller vilka lösningar (avverkningsplaner) som bäst svarar mot satta leveransmål.

För att förbättra planeringens robusthet har olika strategier implementerats inom ramverket för att hantera variationer i vägarnas tillgänglighet och för att minska variationerna i leveranser. Ett angreppssätt är att minska variationerna mellan månatliga inleveranser, vilket kan hanteras i optimeringen. Ett annat sätt är att utvärdera hur robust en avverkningsplan är i olika vädersituationer, genom att undersöka hur bra den presterar mot satta leveransmål i olika väderscenarion, som i sin tur påverkar vägtillgängligheten.

För att visa hur ramverket skulle kunna användas i praktisk tillämpning har förslag på webgränssnitt presenterats som prototyper. De visualiserar hur en praktisk implementation skulle kunna se ut och kunna göras. I optimeringen används genetiska algoritmer. Nackdelen är att de kan vara tidskrävande, där tillgången till datorkapacitet förbättrar beräkningstiden. Genom användandet av tillfällig datorkapacitet ”på begäran” har beräkningarna kunnat snabbas upp betydligt, vilket är tillämpbart även i en praktisk implementering.

Slutligen förslås en systemdesign för operativ planering, där digitala tvillingar och artificiell intelligens integreras i ramverket för att hantera realtidsosäkerheter som en del av nyligen initierad forskning. Denna vidareutveckling bygger i grunden på ramverket med avverkningsplanering för fler mål, men där transporter kan anpassas efter aktuellt väder för att klara uppsatta långsiktiga leveransmål.

Forskningens huvudsakliga bidrag är en flexibel metodik inom ramverket för simuleringsbaserad flermålsoptimering, som stödjer varierande mål och lösningsalgoritmer. Detta tillvägagångssätt möjliggör förbättring av flera samtidiga leveransmål i avverkningsplaneringen, samtidigt som osäkerheter hanteras och ger förslag på hur ramverket skulle kunna se ut i en verklig implementation.

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