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ANALYZING DELIVERY PERFORMANCE AND ROBUSTNESS OF WOOD SUPPLY CHAINS USING SIMULATION-BASED MULTI-OBJECTIVE OPTIMIZATION

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ABSTRACT

The wood supply chain is complex, involving numerous stakeholders, processes, and logistical challenges to ensure the timely and accurate delivery of wood products to customers. Variation in road accessibility caused by weather further compounds operational complexity. This paper delves into the challenges faced by forestry managers and explores how simulation and optimization techniques can address these challenges. By integrating simulation with multi-objective optimization algorithms, this research aims to optimize harvest scheduling, addressing multiple conflicting objectives including maximizing service level and throughput, while minimizing lead time and delivery deviation measured as a loss function. The findings underscore the potential of such a simulation-based multi-objective optimization approach to enhance both delivery performance and robustness in wood supply chains, providing valuable insights for decision-making. Ultimately, this research contributes to advancing the understanding of how simulation and optimization techniques can bolster the efficiency and resilience of the forestry industry to face evolving challenges.

1 INTRODUCTION

Wood Supply Chains (Wood-SCs) are inherently complex, involving numerous nodes and processes that must seamlessly collaborate to ensure the timely and accurate delivery of wood products. Various service providers, stakeholders, information sources, customers, forest owners, and logistics providers are involved along the supply chain. Efficient supply chain management, capable of managing stochastic variations, is crucial for ensuring the precise delivery of wood products in terms of on-time delivery and service level, while maintaining the demanded quality. These products, sourced from private forest owners, company-owned forests, state forests, municipal forests, and other public owners, are used in sawmills, pulp mills, as well as heat and power industries. Forest managers must maintain a high service level (SL), ensuring timely delivery of requested products with minimal variation in backorders (BOs) defined as a loss function in deliveries, $E[\iota_{BO}]$. Simultaneously, they aim to shorten the lead time (LT) to ensure the quality of wood products while maximizing the production throughput (TH) of the Wood-SC, all striving to achieve the highest possible delivery performance (DP).

The scheduling of wood flows to industry begins with the sequencing of harvesting sites for harvesting teams. Monthly delivery quotas for different wood products are expected to be consistently met. Each harvesting site has specific conditions such as estimated product volumes, thinning or final felling, and the accessibility to the forest roadside buffers (RBs) dependent on the time of the year. Each site is harvested by a harvesting operations team, comprising a harvester and a forwarder, transporting the wood to the RB. At these buffers, the wood is stored in product piles for pickup and transportation to customers by truck. RBs are strategically placed along forest roads, each with different classifications of bearing capacity based on road construction. Access to these RBs depends on weather conditions, including freezing temperatures, rain, or thawing periods, facing a growing challenge due to climate changes (Lehtonen et al.

2019; Jönsson and Lagergren 2017). These conditions affect road accessibility and the accessibility of RBs throughout the year, necessitating careful consideration in the harvest scheduling. Each harvesting site is assigned the estimated product volumes and in what time periods the RB is accessible (weekly) based on weather and the bearing capacity of the forest roads. During winter, frozen ground allows for transportation on certain roads, whereas thawing periods limit accessibility, affecting wood pickup from some sites. A typical harvesting operation yields lumber that is destined for several different customers for use in different products. Transports from harvesting sites are typically carried out by trucks directly to mills or to terminals for transshipment to boats or trains for long-distance transportation.

Apart from the on-time delivery, the transported products must also meet the required quality, as wood products are particularly sensitive to the time between harvesting and delivery (Rauch et al. 2022). This is especially important in case of warm weather, when the wood quality is sensitive to a prolonged LT. A long LT in the RB can impact wood quality, potentially leading to degradation and failure to meet the customers' quality specifications. For example, the LT is crucial for high-value pine saw logs in warm weather periods, where a prolonged LT can cause blue stains in the logs, degrading them to low-value products such as conifer pulp. Furthermore, the production rate quantified as TH, serves as an indicator of the productivity of the Wood-SC. It indicates how effective the harvest scheduling is for the wood flow in the chain, for a configuration of its constituent parties such as the number of harvesting teams, available trucks, and process times. Therefore, forest managers evaluate the performance of their harvest scheduling based on a number of objectives which are conflicting with each other. Additionally, the harvesting schedule must also be evaluated based on its alignment with the robustness of the deliveries, subject to various uncertainties due to weather and road conditions as discussed above.

This paper explores the role of simulation and optimization techniques in addressing these challenges and enhancing the efficiency and robustness of Wood-SC management. By integrating simulation with multi-objective optimization (MOO) algorithms, this paper aims to optimize Wood-SC operations amid transportation uncertainties due to various weather and road conditions. The present study uses a simulation model developed in an EU project for the Swedish forestry industry to demonstrate the application of such a simulation-based multi-objective optimization (SMO) approach to address conflicting objectives in Wood-SC management, including maximizing SL and TH while minimizing LT and delivery variations. The findings highlight the potential of how SMO can be used to improve both delivery precision and ensure its robustness in order to guide decision-making in planning and operating Wood-SCs.

The remainder of the paper is organized as follows. Section 2 is the literature review, which justifies the research gaps. In essence, any simulation-based optimization approach requires the development of simulation models. Therefore, Section 3 provides details on how a simulation model developed specifically for a Wood-SC can be used to generate multiple objective function evaluations readily connected to MOO algorithms. An SMO framework with the MOO problem formulation for the aforementioned optimization objectives is introduced in Section 4. Initial SMO experiment results, in terms of the Pareto front and its analysis using various visualizations on a dashboard designed for forestry managers, are presented in Section 5, followed by the conclusions and an outline of future work in Section 6.

2 LITERATURE REVIEW

Supply chain planning in forestry for wood procurement spans a wide time horizon, with the majority of examples focusing on long-term planning over several years (Wikström et al. 2011; Forsberg et al. 2013) to daily operational planning (Andersson et al. 2008; D'Amours et al. 2009; Bredström et al. 2010; Bredström et al. 2013; Frisk et al. 2016; Acuna et al. 2019). This planning predominantly employs a variety of optimization methods. Transitioning from a long-term perspective of planning to a more operative scheduling poses a significant challenge. Yet few studies have tackled operational-level planning (Atashbar et al. 2016), particularly when complicated by weather variations affecting the accessibility of the RBs. Within a Wood-SC, scheduling deliveries to customers is intricate. Forest managers are assessed by their DP, which reflects their ability to deliver the right wood products at the right quality and time to customers while maintaining the highest possible production levels in wood flows. One major challenge is to evaluate how different harvesting schedules meet the delivery demands. Effective balancing and prioritization of multiple DP objectives is a crucial task for a forest manager.

Existing research underscores the critical role of DP in supply chains, as evidenced by key performance indicators highlighted by Stewart (1995), Gunasekaran et al. (2001), and Gunasekaran et al. (2004). On-time deliveries are particularly vital in order-to-delivery supply chains, ensuring timely delivery of products while maintaining high production rates. Forslund et al. (2009) emphasize the importance of timely delivery in such supply chains. While the DP indirectly reflects customer satisfaction, the TH directly indicates the supply chain productivity and the impact of scheduling on production and transportation efficiency. Harvest scheduling involves managing divergent product flows and prioritizing the SL for certain customers, potentially impacting the BO and, hence, the DP for others. Thus, optimizing scheduling in the wood supply chain poses a complex optimization challenge to balance these objectives. Storing wood at RBs can expedite deliveries and enhance delivery robustness, but also carries risks of quality degradation. For a forest manager, keeping wood at RBs and increasing the LT to ensure prompt deliveries (low BO and high SL) always entails the risk of reduced accessibility due to adverse weather conditions, potentially leading to degraded wood quality and reduced product value. This risk must be balanced against the risk of delayed deliveries and fluctuating delivery targets, which may incur penalties. Moreover, as discussed in Section 1, the LT performance has to be considered seriously for ensuring quality requirements.

Apart from the DP, customers also expect consistent and robust flows, meaning that variations in deliveries relative to demand should be minimized. Wood flows should remain consistent between months, as sawmills or pulp mills typically maintain a constant production rate. Addressing robustness in deliveries in the Wood-SC context – ensuring that BO variations are minimized – can be accomplished by incorporating a DP objective that minimizes the variations of BO when calculating a Wood-SC harvest schedule. Various approaches are considered for handling uncertainty within supply chain modeling, including scenario-based modeling, sensitivity analysis, stochastic optimization, and robust optimization (Shabani et al. 2013). While deterministic models are deemed effective for modeling forest biomass supply chains, they struggle to incorporate uncertainty parameters. Therefore, the approach presented here is distinguished by embedding robust optimization within the harvest scheduling phase, directly addressing variability in deliveries.

Schmitt and Singh (2009) and Lawson and Leemis (2008) state that Monte Carlo simulation is suited for static systems when the focus of time progression is irrelevant, but discrete event simulation (DES) is ideal for dynamic systems when studying system performance over time is critical. For experimenting with the supply chain parameters, DES is also an appropriate tool for the interpretation of a complex supply chain, like the Wood-SC. The advantage of DES is the possibility to use descriptive input parameters that can vary stochastically with separate probability distributions, as described in the review study by Shabani et al. (2013) in using deterministic and stochastic mathematical models for optimizing forest biomass supply. Sanchez (2000) and Sanchez and Sanchez (2020) discuss the importance of a robust design using the design of experiments and decribe a loss function formulation based on the standard deviation of the target performance index. Examples of combining optimization and simulation remain scarce in Wood-SC scheduling research (Malladi and Sowlati 2017), especially regarding robustness in terms of loss function as an objective (Sanchez 2000).

Wood-SC planning studies often focus on single-objective optimization, mainly cost-oriented, neglecting multi-criteria decisions (Atashbar et al. 2016). Combining DES with optimization offers a way to generate optimal solutions for complex problems, complementing the evaluative nature of simulation with the solution-searching capability of optimization. Kogler and Rauch (2018), Malladi and Sowlati (2017), and Shahi and Pulkki (2013) note the scarcity of studies combining simulation and optimization, and particular multi-objective optimization techniques in Wood-SC planning, stressing the need for further research. Acuna et al. (2019) discuss the potential of multi-objective decision support systems for evaluating various choices, emphasizing the integration of optimization and simulation techniques in operational planning. They argue that such systems can significantly aid decision-making in forestry contexts by enabling assessment across diverse objectives. Despite recommendations for integrating DES with MOO to address conflicting objectives in DP, this approach remains underexplored and few studies have pursued this approach for the Wood-SC (Kogler and Rauch 2018; Malladi and Sowlati 2017; Shahi and Pulkki 2013). The application of multi-objective optimization in the Wood-SC is limited, despite the necessity for forest managers to engage in multi-criteria decision making for a robust DP. To address this research gap, the present study further develops the simulation-based multi-objective framework proposed by Westlund et al. (2024b) by incorporating a robustness objective to address variations in deliveries. This approach enhances the capability of the framework to present Pareto-optimal solutions that effectively balance multiple DP objectives, ensuring both optimal and robust harvest schedules.

3 A SIMULATION MODEL FOR THE WOOD-SC

A DES model is developed using the FACTS Analyzer based on an earlier version of a Wood-SC DES model developed in the Greenlane project (Westlund et al. 2024a) (Figure 1), which encompasses all major forestry activities described earlier in this paper. Unlike any mathematical modeling, such a DES model enables the logging of data at various points in the flow: SL for deliveries, TH for wood flows, LTs for harvesting, forwarding, RB, and transport are logged and aggregated to determine the total LT. Variant-dependent BO is tallied for each product assortment and aggregated monthly for assessing the scheduling performance. Unmet product order volumes are recorded as monthly BO; BO and LT are measured separately for different wood products to track and analyze the performance on individual product types.

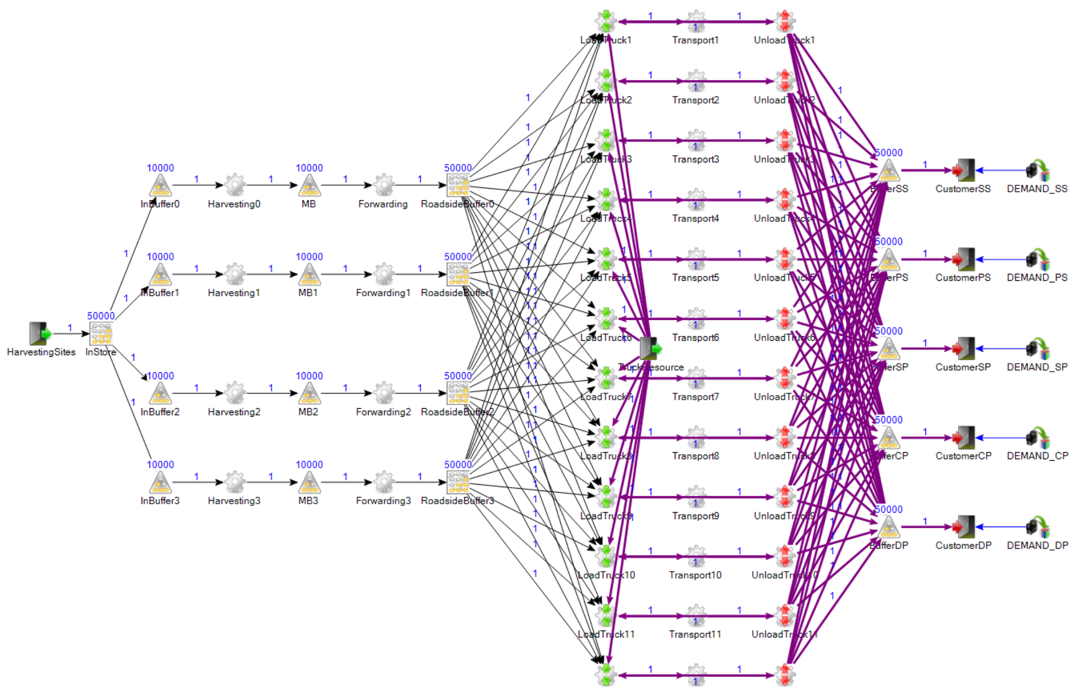


Figure 1: The DES model in the FACTS Analyzer of the studied Wood-SC.

This DES model allows the evaluation of the multiple objectives required in the SMO. It is used to model and analyze the DP objectives from a harvesting schedule throughout a year using DES. DP objectives include LT and SL per product assortment (Westlund et al. 2024b), the TH of wood and the variations in BOs. Monthly SL are calculated as unfulfilled demand for each product assortment by the end of the month and the deviation from demand as σ^2_{BO}. The average LT is computed as the total time it takes for a 40 m³ load to traverse from harvesting through forwarding, RBs, and transport to customers.

Harvesting involves converting standing trees into products, which are then transported to the roadside during forwarding. The harvested products can be broadly categorized as spruce logs, pine logs, spruce pulpwood, conifer pulpwood, and deciduous pulpwood. In a general Swedish Wood-SC, saw logs are cut according to sawmill specifications, while pulpwood is a bulk assortment. Product volumes in a stand are estimated based on tree characteristics determined through inventories. These pre-harvest estimates are used for supply planning, determining which mix of stands can fulfill customer demands considering the availability of stands throughout the year. Diverging flows are integral to the Wood-SC because each tree is bucked into multiple products based on diameter and quality dependent on customer demand. The harvester optimizes the bucking pattern for each specific stem, and the logs are picked up by the forwarder and transported to the roadside.

A harvesting plan is developed well in advance, detailing when to harvest each site and for which customer specifications. These plans often cover scheduled harvesting and deliveries for periods ranging from a month to half a year. The harvesting team, comprised of a harvester and a forwarder, operates according to this plan, working in tandem. The forwarder transports the wood products and sorts them into different piles at the RB. Harvester operations occur simultaneously at different sites, with teams moving from one site to another as per the harvesting plan. Both production and logistics costs are tracked per production entity, with harvester team costs measured per unit of wood produced. Harvester production capacity primarily depends on harvested tree size and felling type, while forwarder production capacity is influenced by wood concentration per area, transport distance, number of products, and felling type (Arlinger et al. 2014; Brunberg et al. 2009; Kuitto et al. 1994), which are described in the DES model. Trucks pick up the wood at RBs in the forest, where the accessibility to the RBs is determined for each week, based on historical weather data (Westlund et al. 2024a). The truck transport time is given as a log-normal distribution (Ranta 2002),

Table 1: Truck transport time functions.

Mean	$2 \times \text{Transport distance}/(14.96 + 9.86 \times \log_e(\text{Transport distance}))$	[km/h]
Loading	$\ln \mathscr{N}(0.1, 0.1^2)$	[h/load]
Unloading	$\ln \mathscr{N}(0.1, 0.1^2)$	[h/load]

The performance of the Wood-SC is assessed based on maintaining a high SL in deliveries, and striving for low variations in monthly deliveries (σ^2_{BO}), reducing the LT (Forslund et al. 2009; Pound et al. 2014) and maximizing the TH wherever possible. These considerations, along with estimations of wood product volumes at sites, must align with monthly customer demand to reach a high SL, with minimal variations in σ^2. However, maintaining consistent deliveries and low σ^2_{BO} throughout the month is challenging, even if BO sometimes can incorporate penalties. The deliveries should be robust with only limited fluctuations in deliveries in comparison to demand to maintain the delivery pace to the customers.

The DES model developed for the single-objective optimization study presented by Westlund et al. (2024a) serves as the foundation for the present simulation model with the proposed DP objectives, including the loss function (Sanchez 2000). The design parameter in the objective function is the absolute loss function $\sigma^2_{BO} = (\text{Demand}_{pt} - \text{Deliveries}_{pt})^2$, penalizing deviations of the total estimated harvested volume from the demand for each assortment and time period while guiding the optimization towards schedules compliant with the expected RB accessibility.

4 SMO FOR THE WOOD-SC

Based on earlier work (Westlund et al. 2024b) in using SMO to optimize the DP in a Wood-SC with three objectives, SL, LT, and TH, a MOO approach using NSGA-II (Deb 2011) for generating the harvesting schedule with an additional objective has been carried out in this study. The MOO and DES are tightly integrated for the iterative generation of Pareto-optimal harvest schedules, as conceptually shown in Figure 2. While NSGA-III performs better for many-objective problems, it introduces additional complexity by requiring reference points to achieve a well-distributed Pareto front. In this study, NSGA-II is chosen for its proven simplicity and sufficient efficiency in solving combinatorial problems (Verma et al. 2021). The MOO problem formulation is provided in the following section.

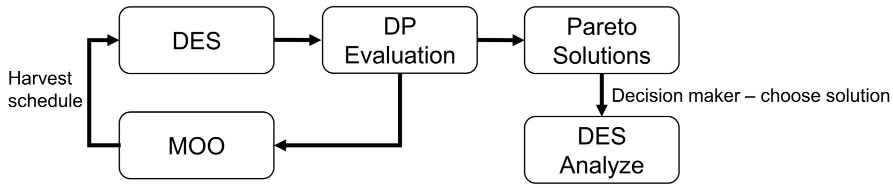


Figure 2: Conceptual model of the SMO.

4.1 MOO Problem Formulation

A MOO problem can be tackled as a single-objective optimization problem by weighting the objectives. Nevertheless, determining the optimal weights of the objectives beforehand poses a challenge. In MOO, trade-offs among solutions are managed by the MOO algorithm, which identifies a set of Pareto-optimal solutions, considering equally important objectives derived from the DES model. The MOO framework manages the trade-offs between these objective values. Supply goals in the Wood-SC may conflict and improving the Wood-SC DP requires understanding how simulation objectives such as SL, LT, and TH interact and counteract. Moreover, an additional fourth objective aims to find solutions to ensure robust deliveries to customers, with a consistent SL across months.

Based on the research of Sanchez (2000) and Sanchez and Sanchez (2020), a loss function $E[\imath_{BO}]$ for the variations in BO was included in the design of the DP objectives and integrated as an output parameter in the DES model. $E[\imath_{BO}]$ is calculated for the deviations in monthly deliveries per product. The DP parameters assess the forest manager through LT, SL, and TH metrics (Forslund et al. 2009; Pound et al. 2014). To enhance delivery commitment robustness and minimize variations, the loss function of the deviation in deliveries, i.e., the variation in deliveries compared to demand, is included in the DP objectives. The four objective functions are computed within the DES model with simulation runs for 12 months and given in Equations 1–4,

N	harvesting sites
T	time period, months, $t = 1, 2, ..., 12$
P	products, $p = 1, 2, ..., P$
D_{pt}	Demanded volume of product p, for time t, $[m^3]$
WD_{pt}	Delivered volume of product p for time t, $[m^3]$
σ_{BO}	Standard deviation in backorders for product p, $[m^3]$
$E[\imath_{BO}]$	Loss function for backorder, with target value 0 m^3

$$\text{maximize} f_1(x) = SL = \sum_{t=1}^{T} \sum_{p=1}^{P} \frac{D_{pt} - WD_{pt}}{D_{pt}} \tag{1}$$

$$\text{minimize } f_2(x) = LT = \frac{1}{P} \sum_{p=1}^{P} \text{entity process time}_p \tag{2}$$

$$\text{maximize} f_3(x) = TH = \frac{1}{P} \sum_{p=1}^{P} \text{TH}_p \tag{3}$$

$$\text{minimize } f_4(x) = E[\iota_{BO}] = \frac{1}{P} \sum_{t=1}^{T} \sum_{p=1}^{P} \sigma^2_{BO_{pt}} + E[BO_{pt}]^2 \tag{4}$$

4.2 Genetic Representation and Partially-Mapped Crossover

The NSGA-II algorithm (Deb et al. 2002) has been a well-known evolutionary MOO algorithm over the last two decades due to its widespread applications in various practical problems (Verma et al. 2021). It was chosen due to its extensive use in solving combinatorial problems similar to the Traveling Salesman Problem. Utilizing meta-heuristic methods like NSGA-II does not guarantee global optimal solutions, but they offer a range of optimized trade-off solutions for decision-makers to consider. This is particularly valuable when the managers' contextual knowledge can be incorporated in choosing from multiple solutions to a problem. NSGA-II operates through two main steps: evaluating each generation of solution populations and refining the replacement of dominant solutions in the next generations. NSGA-II involves comparing and ranking solutions in the objectives space in terms of fronts and crowding distance to encourage diversity within a front. Fronts with the lowest rank, when minimized, indicate better convergence. In the case of this problem, genetic operators for crossover and mutation have been customized specifically for a permutation problem type. The crossover operator combines parents from the mating pool to produce superior offspring in subsequent generations, while the mutation operator recombines individuals in the mating pool for the next population.

The harvest scheduling problem is a permutation problem that requires the use of adequate algorithmic operators. Westlund et al. (2024b) conducted implementations and experiments of multiple genetic crossovers to compare and analyze their convergence efficiency and the quality of generated solutions in terms of the DP. Partially-Mapped Crossover (PMX) (Puljić and Manger 2013) gave the best performance and is used for the harvest scheduling problem in this paper. The PMX crossover ensures that alleles are unique in permutation problems. In this method, two positions, genes, are randomly selected. The offspring inherits the gene sequence from one parent and fills in the rest with genes from the other parent. To ensure uniqueness, the offspring's gene appearance is re-assessed. If necessary, genes are replaced with those from the other parent. An example is given in Figure 3a, where the crossover points are marked. The genes in Parent 2, | 2 9 8 4 |, are copied into the offspring. For the remaining empty positions, genes are copied from Parent 1. To resolve the duplicates, the genes in Parent 2 are mapped to the genes in Parent 1, filling the remaining empty positions. An example of inversion mutation is given in Figure 3b, where a subset of genes is selected randomly and the order is reversed.

5 EXPERIMENT, RESULTS AND ANALYSIS

The SMO calculates Pareto-optimal solutions to be analyzed for the Wood-SC in the DES model. The SMO model ran for a population of 50 over 100 generations with ten replications in each simulation experiment and was executed on a standard laptop, when using one CPU core taking 24 hours generating the Pareto-optimal solutions. The framework can be readily extended to support parallelized simulation runs, so that the optimization time can be significantly reduced. Each simulation is assigned a harvest

Parent 1:	(1 2 3 | 4 5 6 7 | 8 9)	Before mutation:	(1 7 3 | 2 9 8 4 | 6 5)
Parent 2:	(3 7 1 | 2 9 8 4 | 5 6)		↓
Offspring:	(1 7 3 | 2 9 8 4 | 6 5)	After mutation:	(1 7 3 | 4 8 9 2 | 6 5)
	(a)		(b)

Figure 3: Example of (a) PMX crossover, and (b) inversion mutation of chromosome.

schedule, and the DES evaluates the four objectives to provide MOO for generating new populations of harvest schedules. A more-detailed comparison of different harvesting schedules can be conducted using single simulation runs of the specific schedules under comparison. In this case, additional output parameters can be collected in the simulation run with longer model computation time. In this way, DES can provide more details on how a particular harvest schedule affects the Wood-SC. For example, more details of the objectives being considered can be compared across various processes and time spans when provided to the DES. These results are typically used for dashboard visualization (see Section 5.2).

5.1 SMO Results

The solutions from the SMO framework are shown in Figure 4. The parallel plot shows solutions with low values in the loss function together with a high SL, but with LT in the middle segment not among the shortest LTs. The parallel plot reveals solutions with low variations in deliveries with a high service SL on an annual basis alongside an LT in moderate time. Additionally, these solutions exhibit high TH. However, the productivity of the entire supply chain is minimally impacted by the harvesting schedule. Although the TH is included in the objectives, it does not significantly impact the DP of which the performance ranges from 32 to 34 truckloads per hour as shown in Figure 5, not making any relevant difference in practice.

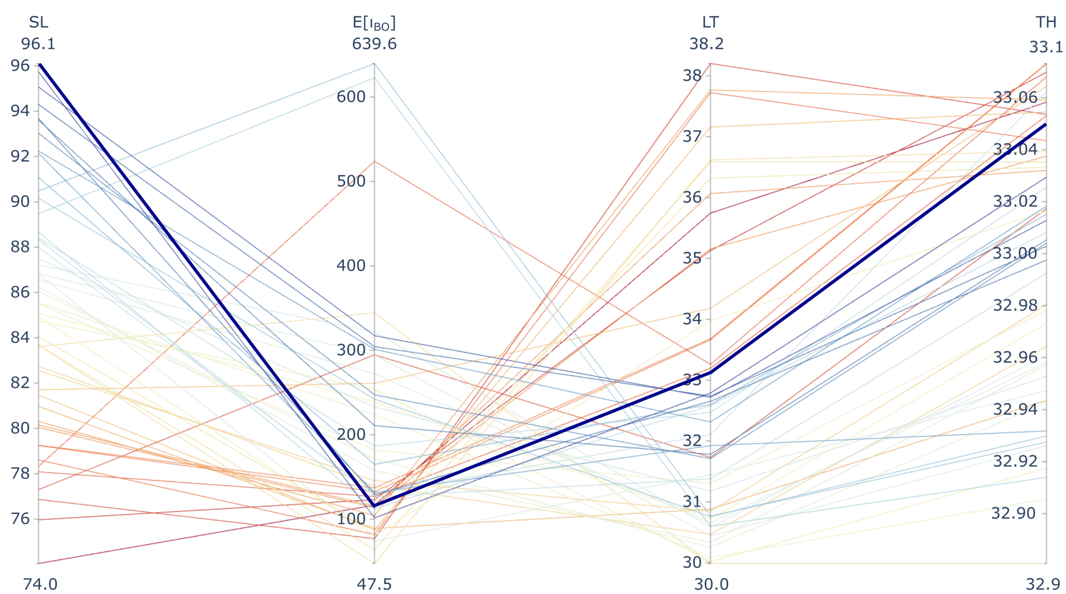


Figure 4: Parallel plot of the Pareto-optimal solutions.

Notably, the productivity of the entire supply chain remains unaffected by the harvesting schedule. More significant is the conflict between the loss function and the LT, where the LT for most solutions becomes longer and ranks among the longest LTs. Most schedules with a lower loss function value have longer LT.

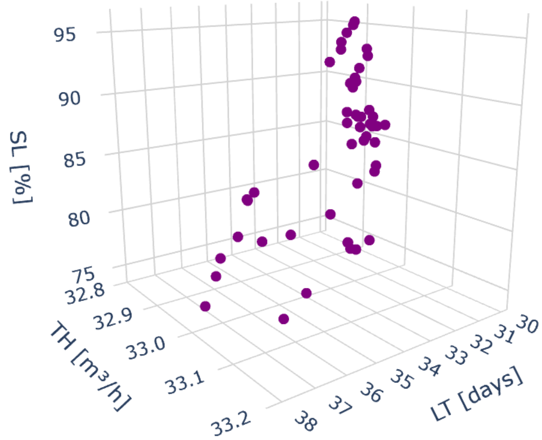
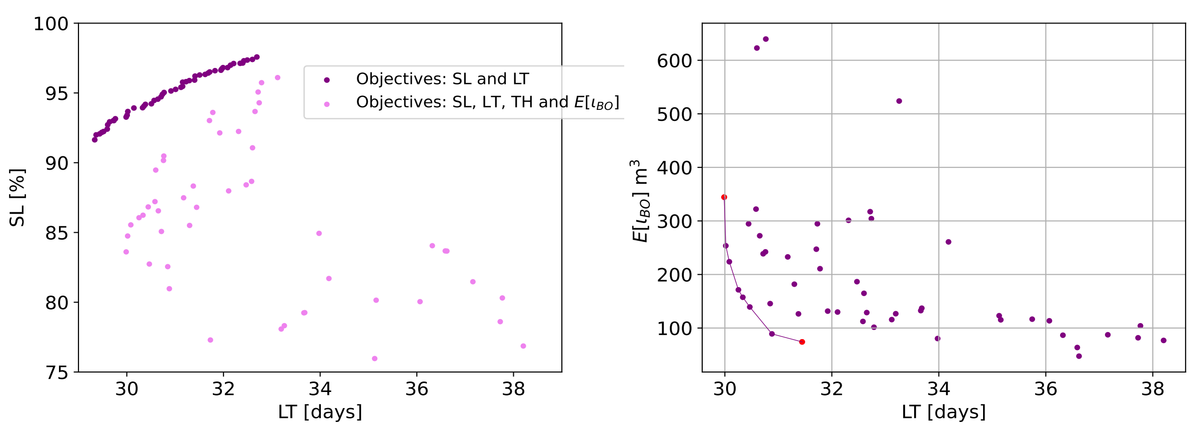


Figure 5: Pareto-optimal solutions in three objectives, showing the range of TH.

In Figure 6a, solutions from two optimization setups are displayed. The purple front represents results from an earlier study (Westlund et al. 2024b) with two objective functions, SL and LT. The violet scatter markers denote optimization results from this study, showcasing outcomes for the added $E[\iota_{BO}]$ and TH objectives. Unlike the first study, the front is less distinct in the results in the present study. Front solutions that resemble those of the two-objectives problem are observed, prioritizing high SL and short LT while minimizing loss in BO. This suggests the feasibility of expanding the objectives to include robustness in BO for finding harvest schedules with less variations in deliveries. Figure 6b shows the relationship between $E[\iota_{BO}]$ and LT, with front solutions highlighted for their minimal LT and $E[\iota_{BO}]$ values. The results suggest that for the majority of solutions – aiming for an LT of at least 32 days – results in consistent delivery variations. However, prioritizing shorter LTs in Wood-SC leads to higher delivery variations, and short LTs come at costs in delivery variations.



(a) (b)

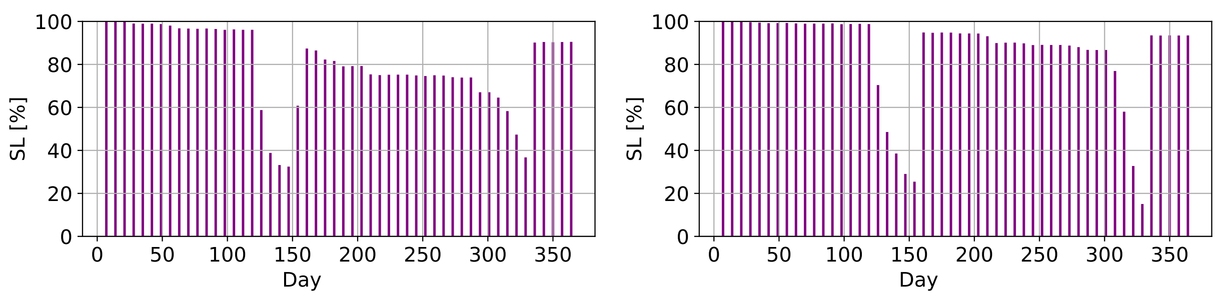
Figure 6: Visualization of the Pareto-optimal solutions: (a) comparsion of two solutions of harvest schedule, from MOO with two and four objectives including $E[\iota_{BO}]$. (b) Pareto-optimal solutions, LT versus $E[\iota_{BO}]$.

5.2 Decision Analysis Using Dashboard Visualization

Pareto-optimal solutions are selected based on the priorities of the decision-makers, e.g., to prioritize minimal variation over a long LT, or to equally balance all objectives. To make an informed decision regarding the choice of a Pareto-optimal solution, it is vital for a forestry manager to thoroughly analyze the solution in detail before making a final decision on the harvest schedule. To analyze a Pareto-optimal solution, the harvesting schedule is simulated in the DES model.

The two highlighted solutions in Figure 6b exemplify how the DES can be used to explore details of a harvest schedule. Two extremes of solutions on the front in terms of $E[\iota_{BO}]$, both with relatively short LT but with differences in the loss function, are simulated in the DES for details of the $E[\iota_{BO}]$ within one year. By simulating the two solutions in the DES model, more details of the DP can be further accessed. An example is shown in Figure 7, where the two highlighted solutions in Figure 6b exemplify how the DES can be used to explore the details of a harvest schedule and are further analyzed. Two extremes of solutions, in terms of $E[\iota_{BO}]$ but with relatively short LT, are simulated in the DES to examine the details within a year. By simulating the two solutions in the DES model, more details can be accessed.

In Figure 7a, the SL for the solution with more variations is shown and with less variations in Figure 7b. The deliveries remain stable at the beginning of the year during winter with frozen ground admitting accessibility to most roads. This holds true for both scenarios depicted in the figures. From March to April, the thawing period begins and many RBs become inaccessible. This phenomenon is clearly observed in the figures, showing a drastic reduction in SL for both solutions, albeit to a greater extent for the solution with higher loss values. Another notable drop in SL occurs between day 300 and 350. This is due to during early fall, heavy rain affects accessibility, leading to road closures and rendering more RBs inaccessible. The reduction in SL is significant during this period, but the drop is rapid and recovery faster to a better SL for the remainder of the year for the solution with a lower loss value. Notably, for the solution with a higher loss value, the SL never fully recovers to the same extent as shown in Figure 7b throughout the year.



(a) (b)

Figure 7: SL for the solutions in Figure 6b: (a) SL ~ 30 days and $E[\iota_{BO}]$ ~ 344; (b) SL ~ 31 days and $E[\iota_{BO}]$ ~ 74 .

6 CONCLUSIONS AND FUTURE WORK

Combining simulation with an intelligent optimization engine allows for the integration of modeling flexibility with the power of optimization, because simulation is not an optimization tool on its own. MOO techniques enable the identification and analysis of trade-off solutions, such as capacity against cycle times in buffer optimization scenarios. The stochastic and variable nature of forestry supply chains suggests that SMO can significantly improve delivery precision and enhance the robustness and flexibility of supply chains, thereby increasing the profitability in the forest industry. By analyzing different scheduling strategies alongside an optimal buffer allocation problem for a supply chain, which is tightly connected to the robustness in deliveries, SMO runs can provide valuable insights and knowledge for scheduling and operating forestry supply chains more efficiently, especially when considering the quality and real-time input data gathered from the forestry fields and the transportation network. One finding from the present study is the difficulty in optimizing the TH, suggesting the potential exclusion of TH as an objective. Reducing the focus on the TH allows for other objectives to be included, thus improving computational efficiency.

A dashboard can visualize both potential solutions for decision-makers and the real-world implications of those decisions or solutions. Through simulation runs of different decision scenarios, a forest manager can explore the detailed effects that a harvest schedule has on processes in the Wood-SC model. This paper proposed an objective for improved DP incorporating robustness into the SMO. To further develop this idea, a division in products and fine-tuning on a monthly or weekly basis is also suggested. This extension aims to provide more detailed insights into the impact of a harvest schedule through an integrated dashboard with which forest managers could experiment with decisions. The framework presented here is suggested as a starting point for the development of such a dashboard decision tool that facilitates forest managers to conduct effective multi-criteria decision analysis and support.

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