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Multi-objective optimization for sugarcane harvesting and processing planning

by

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– Global supply chain management

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Abstract

Sugarcane supply chain planning has been a popular topic in recent years. This thesis studies an integrated sugarcane harvesting and processing scheduling problem in a single-product supply chain focused exclusively on sugar production. The challenge is how to coordinate harvesting and milling operations to achieve both high economic profitability and optimal sucrose yield under limited harvesting and processing capacities. Variability adds complexity on multiple fronts. First, both the sugarcane tonnage and the sucrose content vary over time, both during crop maturation and after harvesting due to post-harvest deterioration. Second, harvest start times differ across plots, affecting both biomass availability and quality. Third, plot sizes are also varied for the heterogeneous model.

These challenges motivate the development of an optimization model, while the presence of multiple stakeholders with differing objectives justifies the use of a multi-objective optimization approach. With the ϵ-constraint method, Pareto frontiers are generated for both the base and the heterogeneous case to examine trade-offs between profit and sugar yield under the variability of harvesting windows and plot sizes. To evaluate solution stability, a robustness check is performed by comparing extreme solutions of maximizing profit and maximizing sugar yield across 10 instances of the base model. Furthermore, an aggregated Pareto frontier for the base model is constructed by averaging across 10 instances, allowing the identification of stable diminishing-return regions and the assessment of how broadly the base-case trade-offs hold under variability in harvesting windows.

A comprehensive sensitivity analysis is conducted to evaluate the impact of key parameters on performance. The tested parameters include the harvesting capacity, harvesting cost, processing cost, disposal cost, selling price, and the length of the allowable processing window. For each parameter, multiple levels are examined to assess their effect on maximum profit solution and the sugar output under the profit max solutions. The analysis identifies thresholds where operational constraints begin to become binding, and how relaxing specific

constraints (such as the processing window) can shift the optimal operating point by allowing greater flexibility in capacity expansion, cost variation, and pricing shifts. The results show that modest relaxation of the processing window constraint yields measurable operational benefits.

The results indicate stable, concave Pareto frontiers across robustness trials. Allowing a limited relaxation of the processing window improves flexibility near sugar-oriented solutions, reducing waste and enhancing profit without compromising yield. These findings provide decision support for capacity-aware, quality-preserving scheduling policies in perishable crop supply chains.

1 Introduction

1.1 Background

The sugar industry has played a significant role in the global economy, because of its direct link to both sugar and ethanol supply. In 2023, global sugarcane production reached 2,025.8 million tons, up from 1,877.8 million tons in 2020, with Brazil, India, China, and Thailand as the top producers (FAO/OWID, 2025). While production has risen, global sugar demand has remained relatively stable, exerting downward pressure on prices (OECD/FAO, 2022). This is especially challenging for countries that have a big market share of their sugar production in the global market. However, recent market forecasts point to short-term volatility, with a projected deficit in 2024/25 due to the reduced production estimate based on the decrease of global sugar price, followed by a rebound in 2025/26 as production expands, especially in Brazil (Asplund, 2025).

In addition to the economic uncertainty, the intrinsic perishability of sugarcane introduces significant challenges at the level of supply chain management. The yield of sugarcane differs in terms of the harvest period, as the overall biomass or fresh weight changes due to a change in growth rate and water content (Lingle and Irvine, 1994). Sugarcane's sugar content is commonly measured using Pol(%), a standard industry indicator of sucrose concentration. The value (Pol%) in the sugar industry varies from 8-15% (Tewari & Irudayaraj, 2003). During the growing period, sucrose accumulates gradually, reaching a peak maturity level before beginning to decline naturally if harvest is postponed. Once the cane is cut, however, sugarcane experiences rapid sucrose deterioration immediately (Solomon et al., 2006). Delays in harvesting or processing can thus reduce sugar quality and overall profitability, emphasizing the importance of just-in-time delivery to mills.

In the sugarcane supply chain, to achieve efficient plans and operations, two main stages of the sugarcane supply chain should be considered in this thesis: 1) sugarcane harvesting (harvesting), and 2) industrial processing of sugar mills

(Teixeira et al., 2023). The sugar industry also involves two main stakeholders, primarily sugarcane growers, and milling companies, whose objectives often diverge: growers seek to maximize cane yield and sucrose quality under agronomic and contractual constraints, while mill operators focus on processing efficiency, cost management and ethanol co-production.

However, in vertically integrated industries with mature ethanol markets, such as Brazil, large mills often own or tightly contract plantations, coordinating harvesting, transport, and processing to optimize both sugar and ethanol production. Land rental agreements are typically time-based and independent of yield or sucrose quality (Pol%), transferring production and quality risk to the mill. In contrast, smallholder-dominated regions like India and parts of Southeast Asia face fragmented landholdings and weaker logistics, making centralized scheduling difficult and highlighting the need for flexible and decentralized harvesting policies. Thailand represents an intermediate case, where contract farming and cooperatives improve coordination but still require policies that can manage numerous small fields.

The sugarcane harvesting and processing in agroindustrial units require a complex and thorough plan and operation, to avoid sugar losses and balance the benefits of growers and mills. Growers decide when and how to harvest the sugarcane, while mills decide when and how to process the sugarcane. Any delays and mismatches between harvesting and milling stages can cause sugar loss. The growers aim to maximize the total sugar content from the yield, and harvest at peak maturity. However, the objective of the mill is to maintain steady throughput, avoid overcapacity, and process the cane with the highest sugar content first in order to maximize their profit. The coordination between harvesting and processing stages need to be considered to avoid quality deterioration and balance stakeholder benefits.

As a result, the harvesting and processing stages are increasingly recognized as critical points for optimization in the sugarcane industry. Developing mathematical models that can integrate logistical and economic variables into a unified planning framework is essential for improving system-wide efficiency, reducing waste, and enhancing stakeholder alignment.

1.2 Research objectives

The primary objective of this research is to develop a multi-objective optimization model that comprehensively addresses the complexities of sugarcane harvesting and processing, integrating multiple stages of the supply chain while balancing the interests of both mills and growers. While optimization models have been used for sugarcane supply chain design and planning, most of these models focus primarily on individual stages, such as harvesting, rather than integrating multiple stages (Teixeira et al., 2023).

As discussed in the background, growers and mills often pursue different objectives, which can create operational bottlenecks during peak maturity periods. Building on this context, the focus is to simultaneously optimize harvesting and processing schedules to maximize sugar yield obtained by farmers and maximize total profit gained by mills, taking into account the temporal dynamics of sugar content in sugarcane. By considering the conflicting objectives of maximizing profit for mills and maximizing sugar yield for growers, the proposed model provides a structured framework for decision making for multiple stakeholders.

A second objective is to apply this model in the comprehensive sensitivity analysis, thereby enabling actionable managerial insights, such as identifying binding capacity constraints, evaluating trade-offs under varying operational conditions, and informing strategic scheduling decisions. The model seeks to effectively manage costs associated with harvesting, transportation, processing, and disposal while ensuring that the optimal harvesting windows are aligned with processing capacities.

1.3 Methodology

This research begins with a literature review to understand current approaches to sugarcane supply chain modeling, operational constraints, and sucrose accumulation and deterioration dynamics. Insights from this review inform the model structure, parameter settings, and experimental design, ensuring that the artificial instances used for computational testing reflect realistic conditions.

In this thesis, a Mixed Integer Programming (MIP) model is built over a finite planning horizon. This framework enables us to incorporate both continuous and binary decision variables that represent key choices of scheduling harvesting activities and allocating processing capacities. An essential feature of the model is the dynamic evolution of sugar content, which typically follows a nonlinear trajectory increasing as the crop matures, reaching a peak, and subsequently declining if harvest is delayed beyond the optimal window. In this thesis, this dynamic behavior is approximated by a linear representation to facilitate integration into the optimization framework. The MIP formulation incorporates key capacity, processing, temporal, and logistical constraints to ensure feasible and efficient harvesting and processing schedules.

For computational experiments, artificial instances will be generated based on parameter settings found in the literature. These instances are meant to reflect realistic scenarios regarding capacities, processing times, and post-harvesting deteriorating challenges. The mathematical model will be implemented in Python and solved using Gurobi. The computational study proceeds in four phases: (1) defining base and heterogeneous instances solvable to optimality within reasonable time; (2) generating the Pareto frontier of base model and heterogeneous model using the ϵ-constraint method to explore trade-offs between profit and sugar yield, focusing on the return-diminishing region, the solution structure, and the capacity utilization; (3) validating robustness by comparing extreme profit-maximizing and sugar-maximizing solutions and averaging their Pareto sets through averaged Pareto sets across 10 random instances; and (4) conducting sensitivity analysis on key parameters.

The structure of the thesis is organized as follows. In Section 1, a brief introduction to sugarcane harvesting and processing is provided. The related literature of different operations in the sugar supply chain is presented in Section 2. In Section 3, we formally describe the problem and present a bi-objective MILP mathematical model. In Section 4, we present computational experiments. The Gurobi solver is utilized to check the robustness of the base model, show the results in Section 5 and perform sensitivity analyses in Section 6. In the last Section, we conclude the findings and limitations of the thesis.

2 Literature review

This chapter critically reviews the literature on sugarcane supply chain optimization, focusing on works that employ mathematical modeling and operational research, as well as selected agronomic studies that directly inform model assumptions or operational constraints. We prioritize studies most relevant to integrated harvesting and processing optimization, multi-objective supply chain modeling, and the handling of key sources of uncertainty. Rather than sequentially summarizing each stage of the supply chain, we compare the main approaches, synthesize their findings, and identify open research gaps.

2.1 Mathematical Optimization Models for Sugarcane Supply Chains

Mathematical optimization plays a central role in improving the efficiency of sugarcane supply chains. While many studies employ mixed-integer programming (MILP), stochastic programming, and multi-objective optimization, most are restricted to single-stage problems of harvesting, transport, or processing, and rarely integrate physiological dynamics explicitly (Teixeira et al., 2023). Existing models typically target objectives such as cost reduction, throughput maximization, or profitability, under simplifying assumptions regarding crop physiology, particularly sucrose dynamics, and post-harvest quality deterioration.

Teixeira et al. (2023), in a systematic review of 56 optimization-focused studies on sugarcane supply chains, show that mathematical programming is widely applied to improve harvest scheduling, transport logistics, and mill processing coordination. However, most models address these stages in isolation, rather than integrating them into a unified framework. These models typically seek to optimize objectives such as cost minimization, profit maximization, or throughput, often under capacity and scheduling constraints. For instance, harvesting models determine the optimal timing and sequencing of field operations to maximize sugar recovery and minimize delays, while transport models address fleet allocation, routing, and delivery timing to reduce logistic costs and product deterioration. At the processing stage, models frequently focus on capacity allocation, scheduling, and inventory management to ensure efficient use of mill resources despite fluctuations in input quality and timing. Stray et al. (2012) develop a seasonal scheduling system of harvesting, transportation, and processing stages, using a time-dependent Traveling Salesman Problem (TSP) framework, allowing adaptive field sequencing under changing climatic conditions. These models typically incorporate capacity constraints, equipment scheduling, and product quality considerations, but often make simplified or static assumptions about crop physiology and maturation.

Multi-objective models are gaining traction for their ability to balance conflicting goals, such as profitability for mills versus sugar yield for growers. Notable examples include the bi-objective MILP of Macowski et al. (2020), which simultaneously considers profit and environmental impact for Brazil's sugar and ethanol supply chain, and the stochastic multi-objective framework of Chavez et al. (2020), which balances operational efficiency and sustainability, accounting for variable yields and resource availability.

Despite these advances, several trends and limitations persist. Many existing models focus on optimizing a single supply chain stage, with relatively few integrating multiple stages. Models that do integrate harvesting, transport, and processing, such as those by Gal et al. (2009) and Bezuidenhout & Baier (2011), highlight significant computational complexity and data requirements, often limiting their practical applicability. Furthermore, the explicit integration of physiological crop characteristics, such as Pol dynamics, maturity curves, or post-harvest deterioration, remains rare, with most operational models relying on fixed or estimated yield parameters.

2.1.1 Sugarcane Planting Optimization

Effective management of the sugarcane supply chain begins with the planting stage, which plays a decisive role in shaping downstream operations and overall productivity. Although much of the literature emphasizes optimization of harvesting, transport, and processing, there are relatively few studies that develop explicit optimization models for planting (Teixeira et al., 2023).

Optimization models for the planting stage are uniquely strategic, focusing on long-term decisions such as field selection, planting calendars, and varietal choice to shape supply chain stability. Rather than optimizing daily operations, these models often formulated as MILP, prioritize the alignment of planting with climate cycles and land characteristics, which directly impacts the efficiency of all downstream stages. For example, Rajput et al. (2023) and Gulati et al. (2015) use such models to enhance yield and sustainability by selecting site-specific planting techniques and optimizing resource deployment at the outset of the supply chain.

Another major theme in the optimization literature is the alignment of planting schedules with agro-climatic windows and varietal requirements, in order to stabilize raw material supply to mills and reduce bottlenecks in subsequent operations. Models incorporating climate and yield forecasting, sometimes through scenario-based or stochastic optimization, are used to identify the best timing for planting and harvesting different varieties, as shown by Viator et al. (2005). Strategic planting density and row geometry decisions, often modeled with MILP or simulation-based approaches, are also important for balancing productivity against operational costs (Bhullar et al., 2002; Rana et al., 2023).

However, most optimization frameworks treat planting in isolation, without fully integrating planting decisions with harvesting and processing schedules. Integrated models, those that link planting-stage planning directly with downstream stages, are rare but increasingly recognized as essential for avoiding supply chain bottlenecks. Studies such as Jena and Poggi (2013) highlight the value of such integration, using advanced data-driven and optimization-based decision support systems to coordinate planting with anticipated demand, harvesting capacity, and processing logistics.

2.1.2 Sugarcane Harvesting Optimization

The harvesting stage has attracted significant attention in the operations research literature, where mixed-integer programming (MIP), metaheuristics, and hybrid models are widely used to optimize harvest scheduling. These models aim to maximize sugar yield, minimize losses from late or early harvesting, and maintain a continuous flow to mills under operational and logistical constraints.

Optimization models for harvesting predominantly apply mix-integer linear programming (MILP) and metaheuristics to maximize yield and minimize logistical delays, with operational constraints such as machinery availability, labor, and mill intake capacity. While agronomic studies establish ideal harvest timing based on sugar content dynamics, operational models typically rely on simplified yield assumptions without fully capturing these dynamics. For example, De Ávila Ribeiro Junqueira & Morabito (2019) developed a MILP model that explicitly considers sequence-dependent setup times for machinery and transport equipment, enabling optimal large-scale harvest scheduling across multiple fields. Similarly, De Ávila Ribeiro Junqueira & Morabito (2019) introduced a hybrid approach that combines heuristics with MIP to dynamically schedule harvest fronts, balancing field readiness, transport availability, and mill processing capacity in real-time. These models demonstrate that integrating multiple operational constraints leads to more efficient and robust harvesting schedules compared to traditional rule-based or sequential methods.

Network and routing models, such as the Traveling Salesman Problem (TSP) or Vehicle Routing Problem (VRP), are central to optimizing sugarcane harvesting, as they enable efficient scheduling of field operations and transport logistics under operational constraints (Morales-Chávez et al., 2016). Additionally, recent research emphasizes the need to adapt harvesting plans to disruptions and uncertainty in yields or logistics, employing robust and stochastic modeling approaches to ensure continuous supply and stakeholder satisfaction (Amaruchkul, 2020).

Metaheuristics such as simulated annealing, genetic algorithms, and two-phase heuristics are frequently used either as standalone approaches or in combination with mathematical programming. For instance, Afifah et al. (2018) applied simulated annealing to optimize harvest-mill matching, minimizing truck use, and maximizing throughput under capacity constraints. Sethanan et al. (2014) developed a two-phase heuristic to optimize harvest front allocation while ensuring both efficiency and equity among growers.

Recent optimization research has increasingly focused on multi-objective and stakeholder-aware models. Beyond single-objective goals such as cost minimization or throughput maximization, newer studies emphasize trade-offs between sugar yield, profit, and operational fairness. As highlighted by Solomon et al. (2006), delayed harvesting and inefficient supply chain coordination can have severe consequences for both growers and mills, underscoring the importance of integrated decision-making that accounts for the interests of multiple stakeholders. Post-harvest sugarcane deterioration affects different actors in distinct ways: farmers suffer from weight loss, millers encounter processing inefficiencies, consumers face reduced sugar quality, and exporters risk penalties due to impurities such as dextran.

To address these challenges, recent contributions have proposed more sophisticated optimization frameworks. For instance, Florentino et al. (2018) developed a multi-objective methodology for sugarcane harvest management that considers varying maturation periods across different varieties. Their approach employs goal programming and metaheuristic methods to balance conflicting objectives, such as aligning harvest schedules with peak sucrose content while efficiently allocating harvesting resources. Complementing this, Aliano Filho et al. (2023) introduced a multi-objective framework for integrated cultivation and harvesting planning, using Pareto-based methods to evaluate trade-offs between profitability and resource utilization. These advances demonstrate how multi-objective and stakeholder-aware models can significantly enhance the realism of harvest planning, enabling more robust, resilient, and fair supply chain strategies.

Despite these advances, key challenges remain. Most models optimize a single stage, often harvesting in isolation, while relatively few fully integrate harvesting with downstream transport and processing operations. Additionally, while some models include simplified crop maturation or post-harvest deterioration effects, the explicit integration of physiological crop dynamics and real-time data remains limited in operational research.

2.1.3 Sugarcane Transportation Optimization

Transportation remains a persistent constraint in sugarcane supply chains, with delays and inefficiencies often leading to increased costs and loss of cane quality. Mathematical optimization, especially mixed-integer programming (MIP), has been widely adopted to optimize truck allocation, route planning, and synchronization between field and mill deliveries (De Ávila Ribeiro Junqueira & Morabito, 2019; Morales-Chávez et al., 2016). Stochastic models further strengthen planning by capturing uncertainties in transport times, worker availability, and crop yields, thus making logistics more adaptable under real-world variability (Amaruchkul, 2020).

Despite these advances, challenges remain in aligning daily transport plans with upstream harvesting and downstream mill operations. Integrated supply chain models (Gal et al., 2009; Carvajal et al., 2019) and digital innovations such as Internet of Things (IoT) tracking are improving coordination, but practical implementation is still limited by system complexity and variable environments.

2.1.4 Sugarcane Processing Optimization

The processing stage is a central node in the sugarcane supply chain, directly transforming raw cane into value-added products such as sugar, ethanol, and bio-energy. Mathematical optimization models for this stage primarily focus on scheduling mill operations, improving throughput, and optimally allocating resources under constraints of quality, inventory, and processing capacity.

In general, sugarcane processing optimization models are formulated as mixed-integer linear programs (MILP), stochastic programs, or simulation-based frameworks. Multi-objective and integrated mathematical models have gained prominence as mills seek to balance economic, quality, and environmental outcomes. Macowski et al. (2020) introduced a bi-objective MILP that jointly optimizes profit and environmental footprint for the Brazilian sugar and ethanol network, coordinating not only feedstock allocation and processing schedules, but also co-product and by-product management across multiple facilities. Similarly, Carvajal et al. (2019) developed a robust optimization framework for integrated agricultural-processing systems, maximizing the net present value of bio-fuel projects under multi-stage climatic and supply uncertainty.

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Stochastic and scenario-based programming have become important tools for handling uncertainties in input supply, processing rates, and market conditions. For instance, Chavez et al. (2020) proposed a multi-objective stochastic optimization model that integrates harvesting, transport logistics, and mill operations, generating Pareto-optimal solutions that account for variability in cane supply, process efficiency, and sustainability goals. Scenario-based planning, as applied by Shavazipour et al. (2020), supports resilient scheduling and investment decisions for bio-ethanol supply chains, allowing planners to hedge against deep market and weather uncertainties.

In summary, recent research underscores the central role of mathematical programming, simulation, and integrated data-driven models for improving efficiency and resilience in sugarcane processing supply chains. These advancements not only increase throughput and profitability, but also promote environmental sustainability and adaptability within increasingly complex and uncertain production systems.

2.2 Multi-Stage Optimization in Sugarcane Supply Chains

The efficiency and resilience of sugarcane supply chains significantly depend on effective coordination between different operational stages, especially harvesting and processing. Traditional single-stage optimization models, despite their detailed representations, often overlook critical interactions between stages, resulting in operational bottlenecks, unnecessary delays, and diminished profitability. This has led researchers toward multi-stage optimization models that explicitly integrate decisions across different stages, enabling more holistic, adaptive, and realistic operational planning. This section reviews the existing literature on integrated multi-stage models, focusing on harvesting-processing synchronization, and identifies gaps that motivate the approach developed in this research.

2.2.1 Integrating Harvesting and Processing Stages

Recent reviews, such as Patil et al. (2024), identify bottlenecks in mill processing as the main sources of inefficiency and stress the need for integrated operational and planning models. To address these challenges, researchers have developed advanced optimization frameworks that synchronize upstream and downstream decisions.

Building on these integrated frameworks, the integration of the harvesting and processing stages has become a focal point in sugarcane supply chain optimization, as decoupled decision-making between the field and the mill is widely recognized to increase raw material losses, bottlenecks, and inefficiencies across the system. Modern mathematical optimization approaches thus increasingly target the simultaneous coordination of these phases, moving beyond isolated stage optimization toward comprehensive, system-wide planning.

One widely cited approach is the CAPCONN simulation model developed by Stutterheim et al. (2008), which links field harvest schedules with factory operations in a unified simulation environment. By modeling the dynamic interactions between harvesting rates, transportation flows, and mill capacity, CAPCONN enables real-time scenario analysis and adaptive scheduling, supporting decision-makers in identifying and mitigating process bottlenecks as they arise.

Beyond simulation, mathematical programming and multi-objective optimization models have been increasingly used to explicitly integrate harvesting and processing. For example, the multi-objective stochastic model proposed by Chavez et al. (2020) captures uncertainties in crop yield, harvesting times, and mill performance, jointly optimizing the scheduling of harvesting, maintenance, and transportation activities. Their framework produces a Pareto frontier of solutions that balance operational efficiency and sustainability, providing valuable insights for managing trade-offs under real-world variability.

Metaheuristic and evolutionary algorithms also play an important role in integrated planning. Jarumaneeroj et al. (2021), for instance, use a genetic algorithm-based model to coordinate harvest allocation and mill intake, optimizing not only for sugar output and processing efficiency but also for equity among growers. Such models are capable of handling the complex, non-linear interactions inherent in real-world sugarcane supply chains.

Several recent studies have extended these models to include more detailed representations of crop physiology and post-harvest quality loss. For example, robust optimization models by Gilani & Sahebi (2020) account for environmental uncertainties such as temperature and rainfall, explicitly modeling how these factors accelerate or slow sucrose deterioration after harvest with a non-linear time-dependent decay function. Scenario-based planning tools by Shavazipour et al. (2020), on the other hand, represent multiple post-harvest decay trajectories under different operational and climatic conditions, allowing the selection of strategies that perform well in a range of possible futures. In contrast, our model applies a constant-rate linear function in sugarcane tonnage, and in sucrose content before harvest and after peak maturity. Aliano Filho et al. (2023b) incorporated cumulative degree days (GDD) into an integrated harvesting and processing optimization model, using thermal time as a proxy for biological development. Degree days measure the accumulation of heat units above a base temperature, which directly influences sugarcane growth, sucrose accumulation, and post-harvest deterioration. By linking operational decisions to degree days accumulation rather than calendar time, their model captures differences in variety specific maturation and the impact of climatic variability on both field scheduling and mill performance.

Despite these advances, few studies explicitly model the dynamic flow of the sugar content, which are the temporal changes in sucrose concentration during crop maturation and after harvest. Most existing integrated approaches rely on fixed, average, or estimated yield parameters for tractability, rather than tracking the continuous evolution of sugar quality over time. As a result, the dynamic nature of the sugar content, which is central to both field management and mill efficiency, is often simplified or omitted in current integrated planning models.

2.2.2 Comparison of Optimization Models

This section provides a structured comparison of key optimization models and approaches in the sugarcane supply chain literature. Table 1 summarizes representative papers, highlighting modeling techniques, supply chain stages addressed, major constraints and parameters, and the primary objectives targeted by each study.

Table 1: Summary of Key Literature on the Sugarcane Supply Chain.

Reference	Model/Approach	Supply Chain Stage	Quality Decay Consideration	Key Constraints/Parameters	Objectives
Teixeira et al. (2023)	Review (MIP, MILP, stochastic, MO)	All stages	Not applicable	Broad survey	Synthesis of trends
Rajput et al. (2023)	MILP	Planting	No	Land, labor, input allocation	Yield, cost, resource efficiency
Gulati et al. (2015)	MILP	Planting	No	Site-specific planting technique	Resource use, sustainability
Viator (2005)	Scenario optimization	Planting	No	Climate, variety, planting season	Yield, timing
Junqueira et al. (2018)	MILP (seq.-dep.)	Harvesting	No	Machine availability, setup, field sequence	Throughput, schedule efficiency
Junqueira et al. (2019)	Hybrid (MIP + Heuristic)	Harvesting	No	Capacity, timing, transport	Delay, schedule robustness
Morales-Chavez et al. (2016)	VRP	Harvest/Transport	No	Vehicle routes, travel time	Cost, fleet efficiency
Amaruchkul et al. (2020)	Stochastic Programming	Harvest/Transport	No	Labor, yield, lot uncertainty	Robust planning
Afifah et al. (2018)	Metaheuristic (SA)	Harvesting	No	Truck, mill capacity	Throughput, resource use
Solomon (2006)	System analysis	Harvesting	Yes	Delay, quality loss	Loss minimization, quality
Macowski et al. (2020)	Bi-objective MILP	Processing	No	Capacity, co-product flow	Profit, environmental impact
Carvajal et al. (2019)	Robust Optimization	Processing+	No	Uncertainty, processing, capacity	NPV, risk management
Chavez et al. (2020)	Stochastic MO MILP	Integrated	No	Yield, timing, mill capacity	Efficiency, sustainability
Shavazipour et al. (2020)	Scenario-based planning	Processing+	Yes	Market/weather risk	Resilient scheduling, investment
Stutterheim (2008)	Simulation	Harvest/Processing	No	Bottlenecks, rates	Adaptive scheduling
Jarumaneeroj (2021)	Genetic Algorithm	Harvest/Processing	No	Output, equity	Output, fairness, efficiency
Gilani et al. (2020)	Robust Optimization	Harvest/Processing	Yes	Loss, environmental constraints	Value, loss reduction

2.3 Sugarcane Life Cycle and Physiology: Implications for Supply Chain Modeling

A fundamental aspect of sugarcane supply chain optimization is the dynamic evolution of sugar content (Pol%) throughout the plant's life cycle. The physiological processes governing biomass accumulation, sucrose storage, and post-harvest quality loss are central to both agronomic management and supply chain performance. However, most existing operational and optimization models treat the sugar content as a fixed or average parameter, neglecting the temporal and environmental variability that directly impacts the yield, timing, and economic returns. In the following sections, we first examine the agronomic drivers of biomass accumulation and sucrose dynamics, before outlining how our proposed approach integrates these dynamics into harvest scheduling and processing decisions.

2.3.1 Biomass Accumulation and Yield Potential

Sugarcane yield depends primarily on biomass accumulation, influenced by cultivar, agronomic practices, and the environment. Coale et al. (1993) modeled dry matter accumulation in Florida sugarcane, noting a typical grand growth phase of rapid weight gain, with rates up to 0.15 t/ha/day. Donaldson et al. (2008) observed that the planting season and varietal choice affect the final yield and resilience, with some cultivars (such as N14, N21) sustaining high productivity under varying conditions. These studies underscore that planting date and field management fundamentally shape the harvestable mass available for processing, making accurate yield forecasting a prerequisite for effective scheduling.

2.3.2 Sucrose (Pol%) Accumulation Dynamics

A fundamental aspect of sugarcane supply chain optimization is the dynamic evolution of sucrose content (Pol%) throughout the plant's life cycle. Pol levels rise during maturation and typically peak before harvest, tightly linked to both genotype and environmental conditions. Studies show that Pol is a strong predictor of extractable sugar and is closely correlated with the commercial cane sugar (CCS) yield (Sanghera et al., 2017; Patil et al., 2020). Figure 1 illustrates the typical maturity curve of sugarcane, showing how Pol(%) gradually increases during growth and peaks at time t before beginning to decline. For example, Lingle (1999) and Vijayaraghavan (1998) document peak Pol levels around 10–12 months after planting, though timing varies by cultivar and climate. Despite this, most operational and optimization models treat Pol as a fixed or average parameter, neglecting its temporal dynamics and environmental variability. This simplification may reduce accuracy in yield estimation and weaken the effectiveness of decisions related to harvest timing and profitability.

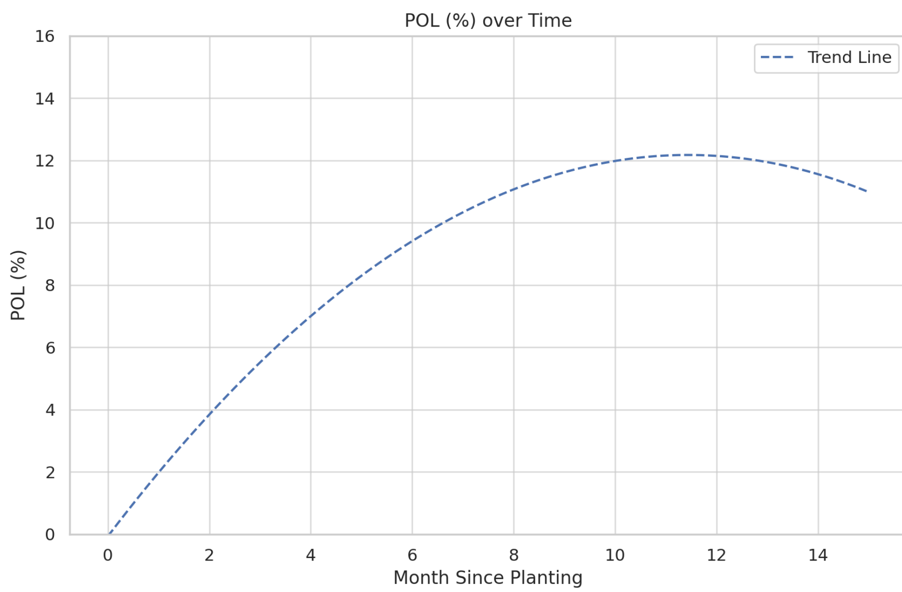

Figure 1: Maturity curve of the sugarcane (adapted from Pimentel Ramos et al., 2016).

2.3.3 Post-harvest Deterioration of Sugar Content

Sugarcane quality deteriorates rapidly after harvest due to biochemical and microbial processes. As shown by Solomon (2009) and Solomon et al. (2006), delays of more than 72 hours between cutting and milling can result in sucrose losses of 8 to 30%, depending on conditions (Figure 2). Enzyme activation

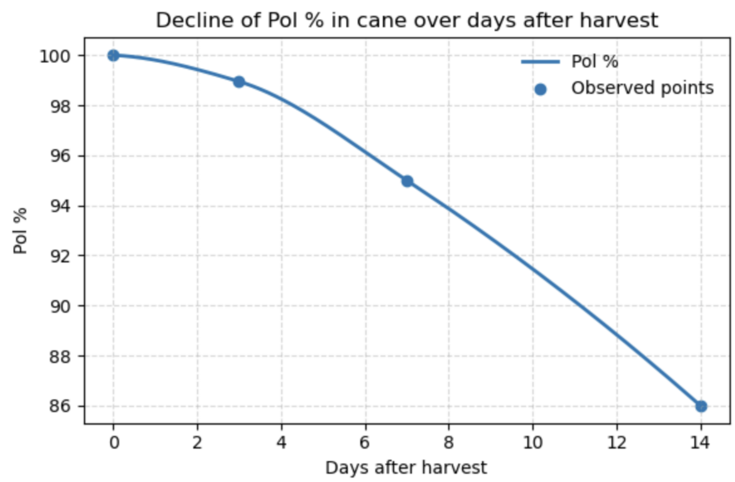

Figure 2: Sugar content decrease due to post-harvest deterioration (adapted from Solomon et al., 2006).

and microbial activity (such as dextran formation) are major drivers of post-harvest losses (Shivalingamurthy et al., 2018). Genotype, storage method, and temperature modulate deterioration rates, with some interventions (such as foliar silicon, invertase inhibitors) reducing but not eliminating losses (Singh et al., 2020). Supply chain decisions that fail to account for rapid post-harvest deterioration risk significant reductions in sugar recovery and overall profitability.

2.4 Link to Current Research: Integrating Physiology with Optimization Models

Despite extensive agronomic research, most existing supply chain optimization models treat yield and quality parameters as static, neglecting the dynamic interplay between biomass growth, sugar accumulation, and post-harvest losses. Few studies explicitly model continuous changes in Pol or link quality dynamics with operational decisions such as harvest timing or mill scheduling. This gap is especially relevant as industry and research have repeatedly demonstrated the economic consequences of delayed processing and non-optimal harvest scheduling.

The present research directly addresses this critical gap by explicitly modeling the continuous temporal evolution of the sugar content (Pol %), capturing both accumulation during maturation and deterioration after harvest. By embedding these physiological dynamics into a mathematical optimization framework, our approach enables precise synchronization between harvesting and processing schedules. The incorporation of these dynamics into the model is achieved by determining the optimal harvesting window for each plot, with details provided in later sections. This integration significantly improves the accuracy, economic viability, and practical relevance of supply chain models compared to previous static-parameter methods.

3 Problem description and mathematical model

3.1 Problem description

This study focuses on the integrated harvesting and processing stage of certain farms over a horizon with discrete time periods. In this section, we develop a multi-objective optimization model for coordinating sugarcane harvesting and processing. Therefore, we present a mathematical model as a tool for determining this plan.

We assume that the problem involves a number of sugarcane plots owned by a set of contract growers. The sugarcane is harvested and transported to multiple sugar mills according to the respective capacity. The scope of the planning comprises two primary stages: the initial harvesting at the farm level and the subsequent transportation and processing at the mill level. Key decisions include determining optimal harvesting schedules, capacity limitations, inventory balances, and processing sequences. Our model aims to reconcile and optimize the interests of both growers and mills, achieving a balanced solution that considers profitability and sugar yield.

3.1.1 Harvesting phase

In this context, we only consider a single variety of sugarcane planted in all plots, which has a one-year growth cycle. In the field, farmers aim to harvest all their plots near the optimal maturity period within harvesting windows to achieve maximum sugar content, directly influencing their revenue. However, since planting times and growth cycles are similar across plots, optimal harvesting periods often overlap, creating a concentrated demand for harvesting equipment, transport vehicles, and processing capacities at the mills. We assume that each plot must be harvested completely within the same period.

A central depot is located among the sugarcane fields, serving as a base for harvesting machines, which are either owned or hired by the milling company. Therefore, the harvesting cost is taken by mills, as a significant part of the profit calculation. The area and sugarcane yield are different for each plot. In the model, harvesting time windows are defined based on the dynamic maturity curves of sugarcane, which describe changes in sucrose content over time. These curves allow the identification of periods in the life cycle of sugarcane when sugar content exceeds a practical threshold for optimal extraction. While this threshold is not implemented as an explicit constraint in the optimization model, it is implicitly embedded through the predetermined harvesting windows: only periods falling after the threshold point on the maturity curve are eligible for harvesting. This ensures that harvesting schedules are synchronized with the biological readiness of the crop, avoiding premature cutting that would compromise yield quality. Each plot is limited to a single harvest per year to preserve consistency in growth cycles, with peak maturity dates varying across plots according to their specific growth trajectories.

3.1.2 Transportation phase

The harvested sugarcane is transported directly to the mills in the same harvesting period using a fleet of vehicles owned by the milling companies. In each period, the fleet of empty vehicles departs from the mill with sufficient capacity, travels to the designated plot for loading, and then transports the harvested sugarcane back to the mill for processing. These vehicles transport sugarcane exclusively from a single plot to a single mill in each trip and can only carry sugarcane with the same sugar content. Each vehicle can do a single back-and-forth trip in each period.

3.1.3 Processing phase

After being harvested and transported in period t, the sugarcane can be immediately processed (in the same period), or it can be kept in storage to be processed later, ensuring that the sugar content does not fall below the minimum acceptable threshold defined by the deterioration curve. This curve, which captures the progressive sucrose loss after harvesting, determines the permissible processing time window for each batch. However, the mills operate under fixed processing capacities, creating potential bottlenecks, especially during peak maturity periods when large volumes of sugarcane are harvested simultaneously. In such cases, only a portion of the available sugarcane can be processed within the designated period, while the remaining quantity is designated as waste and excluded from further processing, aligning with the operational capacity constraints.

3.1.4 Inventory phase

We introduce the inventory variable to represent the tonnage of harvested cane held in store at the end of period t, prior to processing. A stock-balance constraint ensures that, for each period, all harvested and transported cane is either processed immediately or carried forward as inventory for later crushing. Storage is permitted only within the allowable processing time window defined by the post-harvest deterioration curve and the minimum sucrose threshold. This ensures that any cane held in inventory can still be processed before its sugar content falls below acceptable levels.

Holding inventory allows the model to smooth processing loads across adjacent periods, and to moderate capacity bottlenecks during peak harvest, while avoiding sugar content degradation beyond the threshold window. The sucrose loss over time is presented by the deterioration curve, so that any delay in crushing reflects a trade-off between operational feasibility and quality preservation. Storage is restricted both by the mill's physical capacity, to prevent spoilage, and by the quality limits imposed by the deterioration profile.

In our numerical experiments, however, we adopt a just-in-time (JIT) assumption, setting the inventory balance of 0 for all t. Under this regime, every unit of harvested cane must be processed in the same period it arrives, eliminating storage and thereby focusing the analysis on the direct interaction between harvesting schedules and processing capacity.

3.1.5 Objectives

The optimization problem has two primary objectives:

1. To maximize the total profit by balancing revenue from processed sugar against the costs of harvesting, transportation, and inventory, representing the benefits of sugar mills.

2. To maximize the total sugar content harvested at the plot, representing the benefits of growers.

In our model, we make the following assumptions:

1. Sugarcane from a plot can only be harvested once annually.
2. The harvested sugarcane is transported directly to the mills in the same period t of harvest and stored, waiting for processing in the same period t or later.
3. Each vehicle can only transport sugarcane from one plot to one mill in a single period and must carry sugarcane with the same sugar content.
4. Sugarcane must be harvested and processed before its sugar content declines below the minimum threshold.

3.2 Notation and model

In this section, the sets, parameters, and decision variables used in the proposed mathematical model are defined as follows.

Sets:

J Set of sugarcane plots to be harvested.

I Set of sugar mills.

T Set of time periods in the planning horizon.

H_j Subset of time periods during which plot $j \in J$ can be harvested; $H_j = \{a_j, a_j + 1, \ldots, b_j - 1, b_j\}$, with a_j (b_j) denoting the earliest (latest) time period harvesting can begin (be completed) on plot j.

K_i Subset of time periods during which the initial inventory can be processed in mill $i \in I$; $K_i = \{1, 2, \ldots, d_i\}$, with d_i denoting the latest processing time period for the initial inventory in mill i.

P_{hj} Subset of time periods during which the sugarcane plot $j \in J$ harvested in period $h \in H$ can be processed at the mill;

$P_{hj} = \{h, \ldots, c_{hj}\}$, with c_{hj} donating the latest possible processing time period for plot j harvested in period h.

Parameters:

POL_{jhp} Percentage polarization (Pol %) at time period p of cane from plot j, harvested in period h, and processed in period p.

POL_{jh} Percentage polarization (Pol %) at time period h of cane from plot j, harvested in period h.

$POL_{pi}^{initial}$ Percentage polarization (Pol %) at time period p of the stored sugarcane in the initial inventory level, processed at mill i.

POL_{min} Minimum sugar content required in harvesting and processing period.

I_{i0} Initial inventory level at mill i.

M_{hi} Total amount of sugarcane that can be harvested in period h by all harvesting machines for mill i.

q_{jh} Quantity of sugarcane available in plot j if harvested during period h.

V_{jih} Number of vehicles required to transport sugarcane from plot j to mill i during the harvest period h.

TV_{ih} Total number of vehicles available for mill i during harvest period h.

CAP_i^{proc} Total milling capacity of mill i per period.

CAP_i^{inv} Total inventory capacity of mill i per period.

C_{jh}^{harv} Total harvest cost for plot j in harvesting period h.

C_{jhi}^{trans} Total transportation cost per vehicle from plot j to mill i in harvesting period h.

C_i^{proc} Total processing cost per quantity in mill i.

C_i^{inv} Total inventory cost per quantity in mill i.

C_i^{disp} Total disposal cost per quantity in mill i, taking both positive and negative values, depending on whether disposal results in a net cost or a revenue-generating activity.

S_i Selling price per quantity of sugar produced in the mill i (in dollars per unit of Pol).

Decision Variables:

X_{jhi} Binary decision variable, 1 if plot j is harvested in period h and sent to mill i.

Z_{jhpi} Continuous variable for quantity harvested from plot j in period h, and processed in period p at mill i.

I_{ip} Continuous variable for inventory level at mill i at the end of period p.

Y_{pi} Continuous variable for quantity taken from the initial inventory to be processed in period p at mill i.

W_{jhi} Continuous variable for quantity of sugarcane waste harvested from plot j during harvesting period h and transported to mill i.

The proposed model is therefore:

$$\text{Maximize : Sugar Content} = \sum_{j \in J} \sum_{h \in H_j} \sum_{i \in I} POL_{jh}\, q_{jh}\, X_{jhi} \tag{1}$$

$$\begin{aligned}
\text{Maximize: Profit} =& \sum_{j\in J}\sum_{h\in H_j}\sum_{p\in P_{hj}}\sum_{i\in I} Z_{jhpi}\cdot S_i\cdot POL_{jhp} \\
&+\sum_{i\in I}\sum_{p\in K_i} Y_{pi}\cdot S_i\cdot POL_{pi}^{initial} \\
&-\sum_{j\in J}\sum_{h\in H_j}\sum_{i\in I} X_{jhi}\cdot C_{jh}^{harv} \\
&-\sum_{j\in J}\sum_{h\in H_j}\sum_{i\in I} V_{jhi}\cdot C_{jhi}^{trans}\cdot X_{jhi} \\
&-\sum_{j\in J}\sum_{h\in H_j}\sum_{p\in P_{hj}}\sum_{i\in I} Z_{jhpi}\cdot C_i^{proc} \\
&-\sum_{p\in K_i}\sum_{i\in I} Y_{pi}\cdot C_i^{proc} \\
&-\sum_{i\in I}\sum_{p\in K_i} I_{ip}\cdot C_i^{inv} \\
&-\sum_{j\in J}\sum_{h\in H_j}\sum_{i\in I} W_{jhi}\cdot C_i^{disp}
\end{aligned} \tag{2}$$

subject to:

$$\sum_{h\in H_j}\sum_{i\in I} X_{jhi} = 1 \quad \forall j\in J \tag{3}$$

$$\sum_{j\in J} q_{jh}\cdot X_{jhi} \le M_{hi} \quad \forall h\in T, i\in I \tag{4}$$

$$\sum_{j\in J} V_{jh}\cdot X_{jhi} \le TV_{ih} \quad \forall h\in T, i\in I \tag{5}$$

$$I_{ip} \le CAP_i^{inv} \quad \forall i\in I, p\in T \tag{6}$$

$$I_{ip} = I_{i,p-1} + \sum_{j\in J}(X_{jpi}\cdot q_{jp} - W_{jpi}) - \sum_{j\in J}\sum_{h\in T|h\le p} Z_{jhpi} - Y_{pi} \quad \forall i\in I, p\in T \tag{7}$$

$$\sum_{j\in J}\sum_{h\in H_j|h\le p} Z_{jhpi} \le CAP_i^{proc} \quad \forall i\in I, p\in T \tag{8}$$

$$W_{jhi} + \sum_{p\in P_{hj}} Z_{jhpi} = X_{jhi}\cdot q_{jh} \quad \forall j\in J, h\in T, i\in I \tag{9}$$

$$\sum_{p\in K_i} Y_{pi} \le I_{0i}, \quad \forall i\in I \tag{10}$$

$$\sum_{h \in T \setminus H_j} \sum_{i \in I} X_{jhi} = 0 \quad \forall j \in J \tag{11}$$

$$\begin{cases} Z_{jhpi} = 0, & \forall j \in J, h \in T \setminus H_j, p \in T, i \in I, \\ Z_{jhpi} = 0, & \forall j \in J, h \in T, p \in T \setminus P_{hj}, i \in I, \\ Z_{jhpi} = 0, & \forall j \in J, h \in T, p \leq h, i \in I, \end{cases} \tag{12}$$

The objective function (1) assesses the profitability of the growers by maximizing the total amount of sucrose content harvested from sugarcane. The objective function (2) maximizes the profit of sugar mills by balancing revenues from sugar production against costs incurred during harvesting, transportation, and processing. Constraints (3) impose that a plot must be harvested exactly once during the planning horizon. Constraints (4), (5), (6), and (8) consider the harvest, transport, inventory, and process capacity. Constraints (4) relate to the harvesting machine capacity, ensuring that the total harvested quantity from all plots does not exceed the machine's operational capacity during any period. The fleet of track and trail capacity relates to (5), considering that the quantity of sugarcane transported does not exceed the available transportation fleet's capacity for a given mill and period. Constraints (6) ensure that the inventory at mills remains within the defined storage limits. Constraints (8) limit the total amount of sugarcane processed at any given mill during each period.

Constraints (7) are related to the inventory balance, dynamically updating the inventory level over time, accounting for leftover stock, inflowing harvested sugarcane, and outflowing processed quantities and waste. Constraints (9) couple variables W_{jhi}, Z_{jhpi}, and X_{jhi}, making sure that harvested sugarcane is properly tracked and processed. Waste arises from the interaction between the Just-In-Time (JIT) processing constraint and limited mill capacity, which forces some excess cane to be discarded unprocessed because of the time window imposed by the minimum sugar content threshold. The initial inventory is tracked in constraints (10), preventing unrealistic processing of the initial inventory levels at the start of the planning period.

Constraints (11) and (12) define the harvesting variables X_{jhi} and processing variables Z_{jhpi}. Constraints (11) ensures that plot is only harvested within its feasible harvesting periods, while constraints (12) prevent sugarcane from being processed if it was not harvested or if it occurred before or during the corresponding harvesting period.

3.3 Methodology and Implementation: ϵ-constraint method

In order to address the inherently conflicting goals of maximizing profit and maximizing sugar content, this study adopts a multi-objective optimization approach. The ϵ-constraint method offers a transparent and systematic way to generate the Pareto frontier, enabling clear insight into the trade-offs between objectives. The ϵ-constraint method is structured in two stages. The first stage establishes the bounds for sugar content by identifying the maximum and minimum attainable sugar content under the optimization framework. This is achieved by solving two single-objective optimization problems:

1. Maximizing Profit: The first problem maximizes profit without explicitly constraining sugar content. To determine the lower bound for ϵ, we calculate the maximum sugar yield achievable subject to the condition that the profit equals the maximum profit obtained in this problem. This requires solving a secondary optimization problem where sugar yield is maximized while enforcing the profit-equality constraint. The resulting sugar yield represents the highest sugar content compatible with maximum profitability.

2. Maximizing Sugar Content: The second problem solely maximizes sugar content without considering profit as an objective. This provides the upper bound for ϵ, representing the maximum attainable sugar content within operational limits.

In the second stage, the ϵ-constraint method is applied by treating sugar content as a constraint and incrementally adjusting its lower bound. By iterating through a predefined set (20 number points) of ϵ values, ranging from the minimum to maximum sugar content values, the Pareto frontier is generated. The modified mathematical formulation for each iteration is defined as follows:

$$
\begin{aligned}
\text{Maximize: Profit} = & \sum_{j\in J}\sum_{h\in H}\sum_{p\in P_{hj}}\sum_{i\in I} Z_{jhpi}\cdot S_i\cdot POL_{jhp} && (13)\\
& + \sum_{i\in I}\sum_{p\in T} Y_{pi}\cdot S_i\cdot POL^{initial}_{pi} && (14)\\
& - \sum_{j\in J}\sum_{h\in H_j}\sum_{i\in I} X_{jhi}\cdot C^{harv}_{jh} && (15)\\
& - \sum_{j\in J}\sum_{h\in H_j}\sum_{i\in I} V_{jhi}\cdot C^{trans}_{jh}\cdot X_{jhi} && (16)\\
& - \sum_{j\in J}\sum_{h\in H_j}\sum_{p\in P_{hj}}\sum_{i\in I} Z_{jhpi}\cdot C^{proc}_{i} && (17)\\
& - \sum_{p\in T}\sum_{i\in I} Y_{pi}\cdot C^{proc}_{i} && (18)\\
& - \sum_{i\in I}\sum_{p\in T} I_{ip}\cdot C^{inv}_{i} && (19)\\
& - \sum_{j\in J}\sum_{h\in H_j}\sum_{i\in I} W_{jhi}\cdot C^{disp}_{i} && (20)
\end{aligned}
$$

Subject to:

$$\text{Constraints (3)–(12)} \tag{21}$$

$$\sum_{j\in J}\sum_{h\in H_j}\sum_{i\in I} X_{jhi}\ \cdot POL_{jh}\ \cdot q_{jh}\ \geq\ \epsilon \tag{22}$$

Constraints (22) ensure that any feasible allocation of harvest decisions must produce a total sugar yield at least equal to the threshold ϵ. By summing $X_{jhi}\ \cdot POL_{jh}\ \cdot q_{jh}$ over all possible plots, harvest periods, and mill assignments, the left-hand side aggregates the total sugar harvested throughout the entire planning horizon. Imposing this aggregated quantity to be at least ϵ guarantees that, in each run of the ϵ-constraint method, the set of harvested plots and their scheduling decisions collectively satisfy a minimum sugar production requirement. In the two-stage procedure, ϵ is varied between the lower bound (the maximum sugar yield associated with maximum profit) and the upper bound (the maximum attainable sugar yield) to generate the Pareto sets, thereby tracing the trade-off between profit and sugar content.

4 Design of the instances

4.1 Base data instances

To ensure the realism and relevance of our analysis, the base instance is designed to closely reflect typical operational patterns in small-scale sugarcane farming systems. The following data instance setup is chosen to represent the scale and structure most commonly observed in the industry, serving as a practical foundation for scenario analysis and optimization.

4.1.1 Basic time and plot set

In many sugarcane producing regions, harvesting is coordinated among small groups of growers, typically ranging from 2 to 8 per group (Jarumaneeroj et al., 2021). This study focuses exclusively on theses small-scale production units. The model considers a set of 65 plots ($j = 65$), which reflects the common structure with a typical group of 2 to 8 small growers, each managing around 10 plots. In our case, 65 represents the largest instance size that can be solved within the available computational time.

Furthermore, the set of sugar mills under consideration is denoted as:

$$I = [1, 2] \tag{23}$$

representing two major mills that coordinate the intake and processing of harvested sugarcane.

In this context, a 12-month sugar cane variety is considered, which can be harvested early (10-months), mid-late (11-12 months), or late (13-months). Selecting a semi-weekly interval as the time bucket for the 4-month harvesting and planning horizon, we obtain a 32-period time horizon:

$$T = [1, 2, 3, \ldots, 32] \tag{24}$$

The processing window is assumed to be limited to the period in which the harvest is done. This is because the sugarcane operation requires the just-in-time (JIT) strategy, which just restricts the same processing period with the harvesting period. The set is shown by:

$$P_{hj} = \{p \mid p = h,\, h \in H_j,\, p \in T\}, \quad \forall j \in J,\, h \in H_j \tag{25}$$

This set is appropriate for planning decisions concerning sugarcane harvesting and sucrose content management. The main parameters are summarized in Table 2.

Table 2: Key Model Parameters.

Parameter	**Value**
Number of sugarcane plots (J)	65
Number of sugar mills (I)	2
Planning horizon (time periods, T)	32 (semi-weekly periods)

4.1.2 Harvest window

The definition of the harvest window is crucial because it determines the feasible time periods in which each plot can be harvested. It links crop maturity patterns with operational scheduling decisions, ensuring that harvesting aligns with both agronomic and logistical constraints.

The harvesting window for a plot can be formally expressed as:

$$H_j = \{t_j^{start}, t_j^{start} + 1, t_j^{start} + 2, \cdots, t_j^{start} + 7\} \tag{26}$$

where h is an element of H_j and represents a potential harvest time within that window, and t_j^{start} is the start period of harvest window of plot j.

In this modeling framework, each sugarcane plot j is assigned a harvesting window of 8 consecutive semi-weekly periods, corresponding to a 4-week interval within the overall 32-period (16-week) planning horizon. This 8-period window was selected because, according to the sugar content accumulation function, the period during which the sugar content in sugarcane remains above 13% lasts for only 8 harvesting periods, as will be further discussed in Section 4.1.6, reflecting both the biological maturity profile and the practical requirements of harvest scheduling within the model's time horizon. Higher (or lower) thresholds for the sugar content will result in smaller (or longer) harvesting windows.

For each plot j, this harvesting window, denoted by H_j, is generated by selecting a valid starting time t_j^{start} at random from a pre-defined range of 1 to 25, in order to ensure the whole harvest window of each plot within the time horizon. These factors inherently result in varied maturation and harvest schedules across different plots. The model also specifies that highest sugar content occurs around period 5 of the harvesting window, due to the sugar content accumulation function, shown in 3.

Table 3: Harvest Window Parameters.

Parameter	**Value**
Harvesting window length per plot (H_j)	8 periods (semi-weekly periods)
Optimal harvesting maturity (POL %)	Period 5 within the harvesting window

Due to natural variability in harvest timing across locations and the absence of detailed field-level data, each plot's harvest window H_j is generated randomly for our model instances.

The resulting set of random harvesting windows H_j is shown below:

Table 4: Harvesting Windows H_j.

Plots 1–25							
1	[21, 28]	2	[4, 11]	3	[1, 8]	4	[24, 31]
5	[9, 16]	6	[8, 15]	7	[8, 15]	8	[5, 12]
9	[24, 31]	10	[4, 11]	11	[22, 29]	12	[24, 31]
13	[18, 25]	14	[3, 10]	15	[19, 26]	16	[14, 21]
17	[2, 9]	18	[1, 8]	19	[3, 10]	20	[7, 14]
21	[8, 15]	22	[17, 24]	23	[20, 27]	24	[1, 8]
25	[18, 25]						
Plots 26–50							
26	[7, 14]	27	[23, 30]	28	[21, 28]	29	[23, 30]
30	[18, 25]	31	[14, 21]	32	[8, 15]	33	[15, 22]
34	[19, 26]	35	[9, 16]	36	[1, 8]	37	[25, 32]
38	[6, 13]	39	[23, 30]	40	[14, 21]	41	[11, 18]
42	[9, 16]	43	[5, 12]	44	[7, 14]	45	[25, 32]
46	[11, 18]	47	[4, 11]	48	[3, 10]	49	[13, 20]
50	[4, 11]						
Plots 51–65							
51	[12, 19]	52	[12, 19]	53	[20, 27]	54	[9, 16]
55	[2, 9]	56	[24, 31]	57	[15, 22]	58	[18, 25]
59	[4, 11]	60	[13, 20]	61	[3, 10]	62	[18, 25]
63	[10, 17]	64	[21, 28]	65	[20, 27]		

Table 4 provides the assigned harvesting windows for each plot in the base instance. This variation in H_j introduces heterogeneity in harvesting windows affected by environmental and climatic factors in real-world sugarcane supply chains.

4.1.3 Capacity information

In the basic instance setup, the harvesting capacity reflects the use of modern two-row sugarcane chopper harvesters operating under typical field conditions. We assume a group of harvesters working together, based on the standard operational efficiency reported in the literature, which can harvest approximately 850 metric tons of sugarcane per semi-week (Ma et al., 2014, 2013).

The trailer truck used to transport between fields and mills, as described in the product information from Sinotruk International (n.d.), is engineered to support a load capacity in the range of 21 to 30 tons. Therefore, in the base model, we choose 25 tons per trip. Crushing capacity refers to the maximum amount of sugarcane that a sugar mill can crush (process) per unit of time, commonly measured in TCD (tons of cane per day). It directly determines how much sugarcane can be processed into sugar and by-products like ethanol, molasses, and bagasse (Misra et al., 2016). The most common crushing capacity in India falls within the range of 2,000 to 2,500 TCD (tons of cane per day) for modern sugar mills, especially in Maharashtra and Uttar Pradesh (Bhatt et al., 2021). However, since we only consider small-scale plot numbers, 1,000 tons of processing capacity and 500 tons of processing capacity per half-week are assumed for mill 1 and 2 respectively, in Table 5.

Sugar mills aim to operate on a just-in-time (JIT) system, where harvested cane is delivered and crushed within 24 hours, often within 12–18 hours. In line with this operational practice, we assume there is no inventory capacity and no holding cost at the mills; harvested cane is processed immediately upon arrival, so there is no inventory at any point in the model. We assume there is no initial inventory present at the start of the planning horizon.

Table 5: Capacity Parameters.

Parameter	Value
Harvesting capacity (per mill, per period)	850 tons
Processing capacity (Mill 1)	1,000 tons/period
Processing capacity (Mill 2)	500 tons/period
Initial inventory at each mill	0 tons
Vehicle capacity	25 tons/trip
Vehicles available (per mill, per period)	150

4.1.4 Cost and revenue information

The cost and revenue parameters applied in this model are directly aligned with the operational context of the simulated instances and are summarized in Table 6. For each instance, harvesting costs reflect contract rates commonly observed in practice, with Mill 1 and Mill 2 incurring 13.33 and 15.67 CAD per ton, respectively, based on recent field data (Bhatt et al., 2021). Transportation expenses are set at 4.49 CAD per ton for both mills, representing the average cost of moving sugarcane from the farm gate to the mill (Bhatt et al., 2021).

Processing costs are differentiated by mill: Mill 1 operates with a base processing cost of 40 CAD per ton, while Mill 2 faces a higher cost of 55 CAD per ton (Pippo et al., 2007). For disposal, the base scenario assumes that any surplus or residue material incurs no additional cost, as it is either used for energy, compost, or disposed of without significant expense.

Table 6: Cost Parameters.

Cost Type	Unit Cost ($/ton)
Harvesting cost (Mill 1)	13.33
Harvesting cost (Mill 2)	15.67
Transportation cost (both)	4.49
Processing cost (Mill 1)	40.00
Processing cost (Mill 2)	55.00
Disposal cost (both)	0.00

4.1.5 Sugarcane life cycle regarding weight

In this section, we introduce the sugarcane life cycle to track the weight changes of sugarcane. During the establishment phase (first 2 months), the density of the planting and the accumulation of the initial biomass determine the overall productive potential of each hectare and guide early scheduling of machinery and labor.

We establish a relationship between cane tonnage (tons per hectare) and days after planting (DAP) with a linear function by incorporating empirical data from Patil et al. (2004) and Dimov et al. (2022). The initial seed weight per hectare, obtained from mechanized planting trials, is 9 tons/ha (Patil et al., 2004), while the maximum recorded yield at maturity (360 DAP) is 315 tons/ha, as reported in (Dimov et al., 2022).

A linear function was formulated to estimate cane tonnage over time since planting (month 0 to month 13), assuming a constant growth rate throughout the crop cycle. The general form of the function is:

$$Y(t) = Y_0 + r \cdot t \tag{27}$$

where:

- $Y(t)$ = Cane tonnage (tons per hectare) at time t
- Y_0 = 9 tons/ha, representing the initial sugarcane weight at time of

planting.

- $r = 2.94$, representing the growth rate in tons/ha per semi-week.
- t = Semi-weeks after planting

Therefore, the final equation governing cane yield accumulation over time considering the whole planting period from month 0 to 13 with the time interval of half-week is:

$$Y_t = 2.94t + 9 \tag{28}$$

The linear growth function described above, shown in Figure 3 provides the foundation for determining the harvestable cane tonnage for each plot j at every possible harvest period h. However, in the base model, harvesting decisions are made only during the final stage of crop development, spanning from the beginning of month 10 ($t = 73$) to the end of month 13 ($t = 112$), which corresponds to 32 semi-weekly periods in our planning horizon. For every plot, the parameter of sugarcane tonnage q_{jh} is calculated by aligning each harvest period with the corresponding stage in the crop's growth timeline, ensuring that it reflects the actual tonnage accumulated up to that period in the crop's life cycle. As a result, the model's yield input for each harvest window is determined by looking up the crop's total accumulated growth at the appropriate stage, guaranteeing a realistic connection between biological development and operational scheduling.

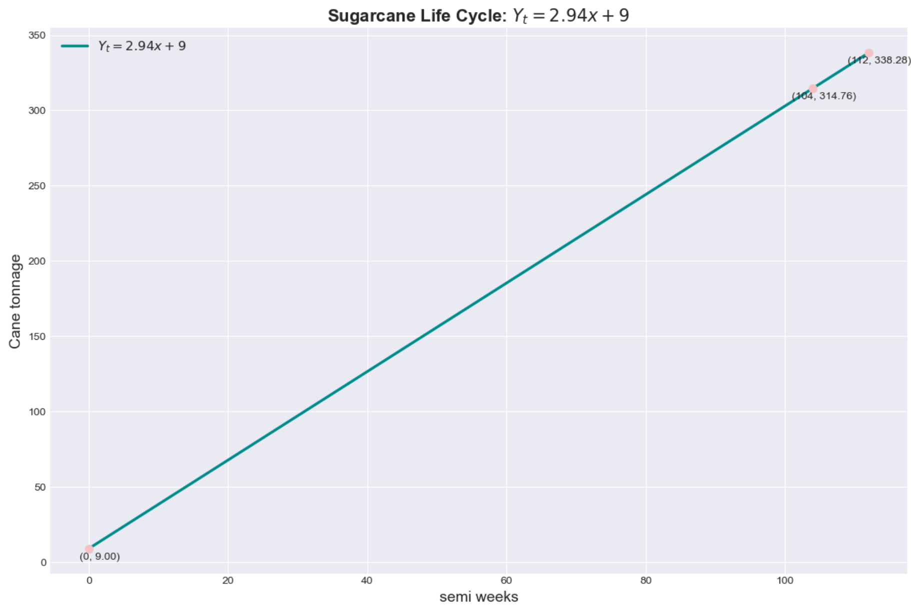

Figure 3: Sugarcane life cycle.

4.1.6 Pre-Harvest sucrose accumulation

Understanding the accumulation of sugar content in sugarcane is essential for optimizing crop management and maximizing yield. Among the various metrics that reflect sugar content, Pol (%), which measures the purity of sugarcane, is widely recognized as a crucial factor directly influencing commercial cane sugar (CCS) (Sanghera et al., 2017; Patil et al., 2020).

The equation represents a piecewise linear model for the pre-harvest accumulation of sugar content of the sugarcane, as a function of time since planting. In this model, the independent variable x corresponds to the number of semi-weeks from planting until harvest, and the model is based on empirical data reported in Vijayaraghavan (1998).

Over the entire pre-harvest period with semi-weeks intervals $0 \leq x \leq 112$, the piecewise model captures two biologically distinct phases of sugar accumulation in the cane:

- Accumulation Phase ($0 \leq x \leq 104$):

In the first 104 semi-weeks after planting, sugar content (S_x) rises approximately linearly:

$$S_x = 0.12\,x \;+\; 1.10 \tag{29}$$

The slope 0.12 (units of sugar per semi-week) reflects steady synthesis of soluble sugars as the stalk matures, and the intercept 1.10 ensures that at $x = 0$ (just after planting) the baseline sugar content is nonzero, which corresponds to the empirically observed peak reported in Vijayaraghavan (1998).

- Decline Phase ($104 \leq x \leq 112$):
  After the physiological peak at period 104, sugar content begins to fall at a faster rate, due to respiration and remobilization:

$$S_x = -0.19\,x \;+\; 33.34 \tag{30}$$

  The negative slope -0.19 indicates a semi-weekly loss of sugar, and the intercept 33.34 is chosen to guarantee continuity at the switch-over point.

Therefore, the equation of pre-harvesting sugar content accumulation since planting shows below:

$$S_x = \begin{cases} 0.12x + 1.10, & 0 \leq x \leq 104 \\ -0.19x + 33.34, & 104 \leq x \leq 112 \end{cases} \tag{31}$$

The piecewise function S_x, shown in Figure 4, which describes the sucrose accumulation and decline in the sugarcane stalk over semi-weekly intervals from planting through physiological maturity, forms the basis for estimating the theoretical maximum sugar content available at each point in the crop cycle. In the optimization model, this biologically driven trajectory is mapped to the variable POL_{jh}, which represents the percentage sugar content (POL %) of plot j if harvested in semi-week h. For each plot, the corresponding x value is determined by the time interval since planting to the scheduled harvest period h.

Applying the piecewise function S_x to this x yields the expected pre-harvest sugar content for each pair (j, h). Table 7 illustrates this relationship, with the overall peak occurring at period 24 within the 32-period planning horizon. Knowing the peak period for each plot allows the model to determine POL_{jh} for every period within its feasible harvest window. This linkage ensures that plot-level harvesting decisions in the optimization framework are grounded in realistic, stage-specific sugar yields that reflect both the natural maturation and deterioration of sugarcane.

Table 7: Pre-harvesting Sugar Content (% POL) by Selected Semi-weekly Periods.

Period (t)	**POL (%)**
1	10.82
4	11.18
8	11.66
12	12.14
16	12.62
20	13.10
24	13.58
25	13.39
28	12.82
32	12.06

To determine the effective harvesting period, a minimum sucrose threshold of 13% is applied to this function. This threshold reflects the lower bound of economically viable processing quality and is derived from industry practice. Using the fitted S_x function, the threshold is first crossed at approximately $x = 100$, 4 semi-weekly periods before the observed peak, shown in Table 8. It remains above this threshold until approximately $x = 107$, three semi-weekly periods after the peak. This produces a total optimal harvest window of eight semi-weekly periods. Within this range, all harvested cane meets or exceeds the required quality standard, allowing for flexibility in scheduling without compromising output quality.

Table 8: Sucrose levels near the peak and corresponding positions in the 8-period harvest window.

Window position	**Time since planting** x	S_x **(%)**
1	100	13.10
2	101	13.22
3	102	13.34
4	103	13.46
5 (peak)	**104**	**13.58**
6	105	13.39
7	106	13.20
8	107	13.01

Figure 4 illustrates the progression of pre-harvest sucrose accumulation, highlighting the precise timing of peak quality. The sucrose content increases steadily, surpassing the 13% threshold shortly before reaching its maximum of 13.58% at semi-week 104. This peak occurs in the fifth semi-weekly period of the harvest window, as indicated by the blue marker. The shaded region represents the full 8 semi-week duration of the harvest window, providing a visual frame for operational scheduling. By clearly marking the peak, the 13% benchmark line, and the harvest window, the chart underscores the importance of aligning harvesting activities with the exact biological maturity stage. This alignment minimizes the risk of quality decline from delayed harvesting, thereby maximizing both sugar content and processing efficiency.

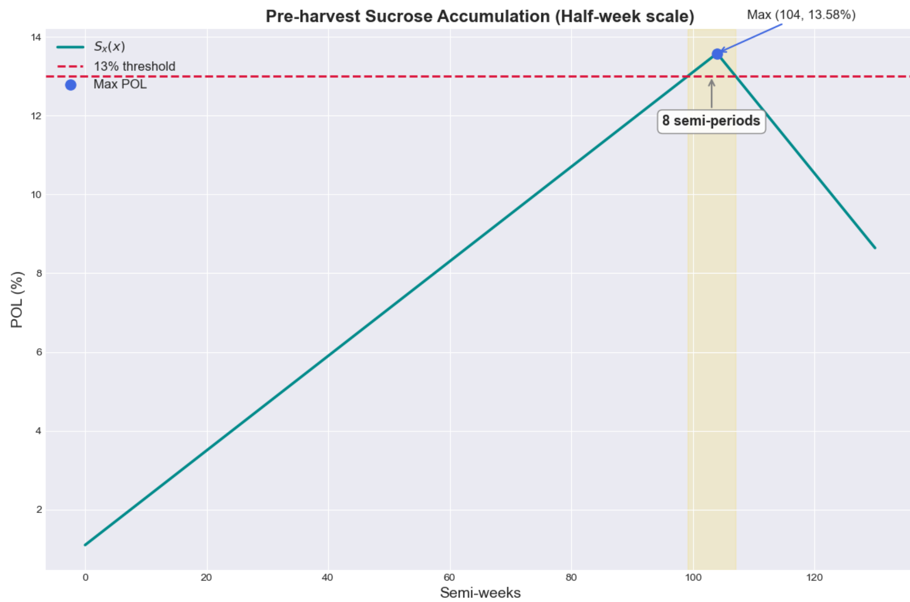

Figure 4: Pre-harvest sucrose accumulation.

4.1.7 Post-Harvest sucrose deterioration

The bio-deterioration in the harvested cane is caused by enzymatic, chemical, and microbial agents and continues to increase with the passage of time. From the four measured POL values at delays of 0 hour, 72 hours, 1 week, and 2 full weeks (respectively 100%, 98.95%, 95%, and 86% (Solomon et al., 2006)), we fixed the intercept at 1.00 and performed a simple least-squares fit to determine a single slope of -0.03225 in the model. The sucrose content in the sugarcane after post-harvest handling is given by, shown in Figure 5:

$$POL_{jhp} = POL_{jh} \cdot [1 - 0.03225 \cdot (p - h)] \tag{32}$$

where:

- POL_{jhp} is the post-harvest POL percentage for the plot j if the harvest is done at time h and the processing is done at time p.
- POL_{jh} is the POL percentage for plot j if harvested is done at time h.

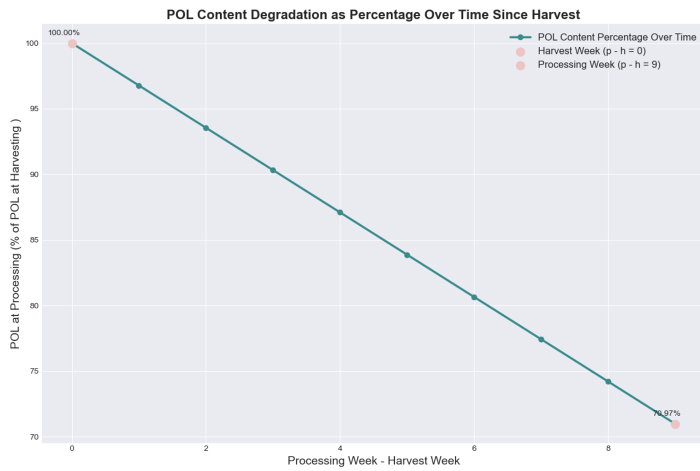

Figure 5: Post-harvest sucrose deterioration.

4.2 Heterogeneous instance setup

To better capture the heterogeneity observed in real-world sugarcane operations, we explore alternative instance setups that extend the base modeling framework. These setups are designed to test the robustness of model outcomes and to examine how key operational and biological variations influence supply chain performance. In the heterogeneous scenario, we retain the same randomized harvest window configuration used in the base instance, while it further introduces controlled randomness in plot size, allowing it to vary within a specified range rather than remain fixed as in the base case. This combined variability in both harvesting windows and plot sizes creates more diverse operational scenarios. By systematically altering these aspects, we can provide deeper insights into decision support for small-scale sugarcane farming, under diverse field and logistical conditions.

4.2.1 Heterogeneous harvest window and plot size

In this section, in addition to the previously considered variability in harvest windows, we introduce plot size as another key source of variability between plots. In the base instance, all sugarcane plots were assumed to have a uniform size, with a size factor of 1.0 applied to every plot; thus, the yield quantity for each plot, q_{jh}, was identical except for temporal growth effects. However, real-world sugarcane production is characterized by significant heterogeneity among field plots, driven by differences in land area, soil conditions, and management practices.

Specifically, each plot j is assigned a randomly drawn size coefficient $A_j \in [0.8, 1.2]$, reflecting variability in plot productivity, as shown in Table 9. This means some plots are smaller (yielding only 80% of the baseline), while others are larger (yielding up to 120%). For each plot j, this multiplier is applied directly to its base yield trajectory, so the effective quantity harvested in each period becomes $A_j \times q_{jh}$, where A_j is the plot's randomly assigned size factor.

The heterogeneous plot size instance is shown below:

Table 9: Plot-Size Coefficients A_j by Plot Range.

Plots 1–25									
1	1.15	2	0.94	3	0.88	4	0.83	5	1.06
6	1.11	7	1.19	8	1.14	9	1.15	10	0.95
11	0.98	12	1.13	13	0.87	14	0.94	15	1.07
16	1.08	17	1.07	18	0.83	19	1.05	20	1.01
21	0.90	22	0.98	23	0.91	24	1.17	25	1.08
Plots 26–50									
26	0.89	27	0.93	28	1.11	29	0.82	30	1.13
31	1.12	32	0.96	33	0.83	34	1.17	35	1.03
36	1.09	37	0.89	38	1.00	39	1.15	40	1.06
41	0.86	42	0.86	43	1.10	44	1.02	45	1.10
46	0.97	47	1.03	48	0.94	49	1.20	50	0.86
Plots 51–65									
51	1.00	52	1.10	53	1.14	54	0.86	55	0.86
56	1.07	57	1.04	58	0.95	59	1.04	60	0.99
61	0.90	62	1.02	63	1.18	64	1.07	65	0.85

This heterogeneous design captures the interactive effects of temporal and spatial heterogeneity among fields and allows us to evaluate how variability in both maturation timing and field size jointly influences scheduling flexibility, resource utilization, and system performance.

5 Result analysis

This section evaluates the computational results of the proposed optimization model, examining solution quality, performance, and trade-offs between objectives. It begins with the solver configuration, followed by robustness check, and scenario-based comparisons to assess how changes in parameters and constraints affect profit, sugar yield, and resource utilization.

5.1 Computational Configuration and Solver Settings

The computational framework is configured using the Gurobi optimizer, with key parameters adjusted to enhance computational efficiency.

In the run, the model was solved using eight parallel threads (Threads = 8) and setting Presolve = 2. MIPGap = 1e-6 demands a very tight optimality tolerance (0.0001%), so Gurobi will continue branching until the best bound and the incumbent solution differ by less than one millionth of the incumbent's objective value.

5.2 Base instance analysis of Pareto Frontier

The full MILP model initially comprises approximately $141,568$ decision variables, including $4,160$ binary and $137,408$ continuous variables, together with over $134,000$ constraints and $143,838$ non-zero parameters. After applying Gurobi's presolve routines, the problem size is dramatically reduced: the solver reduces the model to about $3,250$ variables and $1,350$ constraints.

For the base model, Table 10 presents the two extreme point solutions generated by the model: maximizing profit versus maximizing sugar content.

In the Max Profit Solution, the harvest and processing schedule is optimized solely for economic return, resulting in the highest achievable profit ($582,265.55), but at a slightly reduced total sugar output (2,726.03 tons). Conversely, the Max Sugar Content Solution prioritizes maximizing the total sugar delivered to the mills, which increases the aggregate sugar output to 2,779.57 tons, but at the cost of a notably lower profit ($477,808.87).

In the Max Profit Solution, the optimization prioritizes economic return by aligning harvesting and processing schedules to maximize revenue. This results in the highest profit ($582,265.55) but yields a slightly lower total sugar output (2,726.03 tons). Structurally, nearly all plots are harvested and delivered to Mill 1, which has a lower processing cost, and most are scheduled for early or mid-period harvests to avoid deterioration and reduce disposal or loss. This schedule minimizes transport and processing costs and tightly synchronizes field activities with mill capacity, producing no waste and no disposal at the mills.

In contrast, the Max Sugar Content Solution adjusts the harvesting strategy to extract the absolute maximum amount of sugar from the crop, raising total sugar delivered to 2,779.57 tons, but at the cost of a significantly reduced profit ($477,808.87). The structure of this solution is noticeably different: to reach higher Pol% values, a substantial share of plots is harvested later in the planning horizon, often just before or during peak maturity periods. This means that part of the harvested plots is transferred to Mill 2, which has a higher processing cost. This results in a more scattered and less synchronized harvest schedule, with more plots delivered to Mill 2, especially during late periods. Additionally, there is a marked increase in disposals, as plots harvested later risk exceeding milling capacity, leading to some cane being left unprocessed or wasted.

The trade-off for this instance highlights a classic operational dilemma: maximizing technical yield (sugar output) requires accepting higher operational costs due to increased use of expensive processing and higher disposal, while maximizing profit encourages earlier harvesting and prioritizes deliveries to the lower-cost mill, resulting in a tighter, more cost-efficient logistical flow with minimal disposals, even if this means not always harvesting at the absolute peak Pol%.

Table 10: Comparison of Max Profit and Max Sugar Content Solutions.

Solution	**Profit ($)**	**Sugar Content (tons)**
Max Profit Solution	$582,265.55	2,726.03
Max Sugar Content Solution	$477,808.87	2779.57

The Pareto frontier generated by employing the ϵ-constraint method in Figure 6 reveals a clear trend: as sugar content harvested by farmers increases, total profit obtained by the mills generally decreases.

Table 11: Pareto Frontier: Trade-off Between Profit and Sugar Content.

#	**Profit ($)**	**Sugar (tons)**
1	582,265.55	2,726.03
2	580,980.62	2,734.48
3	579,376.56	2,742.93
4	577,171.48	2,745.75
5	577,171.48	2,748.57
6	577,171.48	2,751.39
7	573,953.46	2,754.21
8	573,953.46	2,757.02
9	570,139.00	2,759.84
10	569,823.46	2,762.66
11	566,303.39	2,765.48
12	561,877.69	2,768.29
13	557,438.74	2,771.11
14	552,288.90	2,773.93
15	529,696.65	2,776.75
16	477,808.87	2,779.57

In Table 11, the Pareto frontier begins with the pure profit-maximization scenario (Point 1), where profit is highest at $582,265.55 and sugar delivered totals

2,726.03 tons. As the constraint on sugar content becomes tighter, only small reductions in profit are required to achieve noticeable gains in sugar yield. For example, at Point 2 (2,734.48 tons of sugar), profit remains at $580,980.62, a loss of just about $1,285 (0.22%) compared to maximum profit. This demonstrates that modest adjustments in harvesting schedules, such as reallocating a few plots to periods of marginally higher Pol(%), can improve sugar output without materially increasing operational costs.

Within the middle range of the frontier (Points 3 to 8), sugar content increases from 2,742.93 to 2,757.02 tons, while profit declines from $579,376.56 to $573,953.46. Here, an additional 14.09 tons of sugar is gained for an approximately $5,423 drop (0.94%) in profit. This moderate trade-off arises mainly from increased mill utilization and higher transport or processing intensity, but still reflects operational strategies that keep costs under control while supporting both mill and grower interests.

As the model shifts further toward maximizing sugar content, profitability decreases more steeply. For example, between Points 10 and 13, the sugar content rises from 2,762.66 to 2,771.11 tons, while the profit drops from $569,823.46 to $557,438.74, a decline of about $12,385 (2.17% decrease) for an added 8.45 tons of sugar (0.31% increase). This sharper reduction reflects the diminishing returns of sugar output: achieving maximum Pol requires pushing more cane to later harvests, often resulting in higher processing costs at less efficient mills.

At the extreme end, the maximum sugar content solution (Point 16) delivers 2,779.57 tons, but profit drops significantly to $477,808.87, which is over $104,000 less than the pure profit solution. This steep decline highlights the costliness of maximizing sugar yield at all costs, as it requires a substantial portion of the crop to be processed under less favorable economic and logistical conditions.

Achieving maximum Pol requires pushing more cane to later harvests, but according to the cost structure in Table 12, this shift leads to a slight increase in processing cost share (from 69.42% in the profit maximizing solution to 69.54% in the max sugar solution) and a minor rises in harvesting costs (from 22.92% to 23.10%). Transport costs actually decrease slightly (from 7.66% to 7.36%).

Thus, the pursuit of a higher sugar content increases total cost mostly through small changes in harvesting and processing, rather than a substantial change in cost structure or efficiency.

Table 12: Cost-structure breakdown (percentage of total cost).

Cost Component	**Max Profit**	**Max Sugar**
Harvesting	22.92%	23.10%
Transporting	7.66%	7.36%
Processing	69.42%	69.54%
Initial Processing	0.00%	0.00%
Inventory Holding	0.00%	0.00%
Disposal	0.00%	0.00%

For decision-makers, the Pareto set offers practical guidance. A mill focused on profitability should operate near Point 1 or Point 2, where incremental sugar gains are possible at minimal profit loss. If the goal is to incentivize higher sugar content (POL %) for growers, intermediate solutions such as Point 8 may be preferable: profit declines by about \$8,312 (from \$582,265.55 at maximum profit to \$573,953.46 at Point 8), while sugar content increases by approximately 31 tons (from 2,726.03 to 2,757.02 tons). Accepting this moderate revenue reduction allows mills to reward growers for delayed harvesting, strengthening the supply relationship.

In summary, the Pareto frontier demonstrates that while higher sugar content can be achieved, it comes at the cost of lower profitability, especially when pushing beyond the mid-range of possible solutions. Strategic compromise points allow mills to balance economic objectives with grower incentives, supporting sustainable and mutually beneficial supply chain operations.

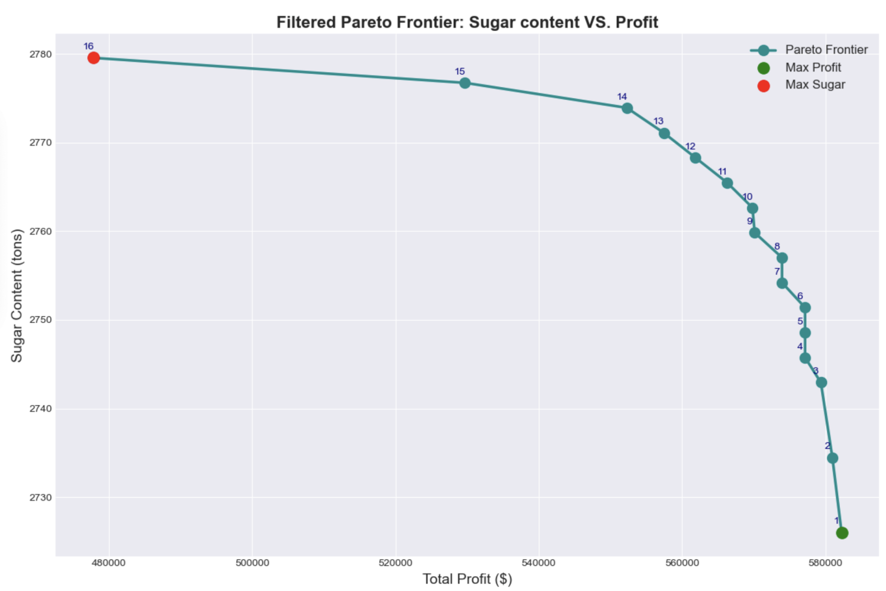

Figure 6: Pareto Frontier: single instance with random harvest window.

5.3 Heterogeneous instance analysis

5.3.1 Heterogeneous instance analysis and Solution Characteristics

In this section, we present the results for the heterogeneous instance setup in Section 4.2, in which we introduce additional sources of real-world variability by randomizing both the harvest window assignments and the plot sizes (within the range [0.8, 1.2]) for each plot, shown in Table 13. Unlike the base instance, where all plots have the same size, this setup reflects more realistic variability in field conditions and harvesting window. The objective is to assess how these changes affect the profit–sugar trade-off and operational pressures on harvesters, mills, and transport fleet. We analyze changes in maximum profit and sugar output, shifts in the Pareto frontier, the resulting capacity utilization in harvesting, processing, and transport, and the structure of solutions.

Table 13: Structural Comparison of Base and Heterogeneous Instances.

Model Feature	Base Instance (Instance #1)	Heterogeneous Instance (Instance #2)
Plot Size Distribution (A_j)	Fixed: $A_j = 1$ for all j	Randomized: $A_j \in [0.8, 1.2]$
Harvest Window Assignment (H_j)	Randomized independently per plot	Randomized independently per plot
Processing Flexibility	No inventory; immediate processing	No inventory; immediate processing
Number of Instance Realizations	Single deterministic case	Heterogeneous realizations
Related Pareto Table	Figure 6	Figure 7

The comparison between the base instance (Table 11) and the heterogeneous instance with heterogeneity of harvest windows and plot size (Table 14) highlights substantial performance improvements enabled by increased flexibility. In the base case, the maximum achievable profit is \$582,265.55 with 2,726.03 tons of sugar delivered, whereas in the heterogeneous instance, the maximum profit rises to \$612,414.46 and the corresponding sugar output to 2,775.20 tons. At the other extreme, maximizing sugar content yields 2,807.62 tons and \$504,933.86 profit in the heterogeneous case, compared to 2,779.57 tons and \$477,808.87 in the base case.

Across both the base and heterogeneous instances, the general pattern of solutions for the Max Profit and Max Sugar Content objectives remains consistent. In both cases, maximizing profit encourages early harvesting and allocation of the majority of plots to Mill 1, which is associated with lower processing costs and greater profit margins. When the objective shifts to maximizing sugar content, both instances exhibit a tendency to delay harvests, shifting more plots toward the latest allowable periods to capitalize on higher sugar yields, with an increasing number of assignments to Mill 2 as Mill 1 reaches its processing limits.

The introduction of combined variability (via randomized harvest windows and variable plot sizes) does not fundamentally alter these overarching strategies, showing the same trajectory for the Pareto frontier in Figure 7, while it simply increases the operational complexity. In the heterogeneous instance, assignments to Mill 2 and the frequency of disposals both rise slightly (Table 15), reflecting more fragmented harvesting schedules and tighter capacity constraints. However, the core logic remains constant: profit-maximizing solutions cluster harvests early and favor the more efficient mill, while sugar-maximizing solutions prioritize late harvest and accept higher logistics and disposal costs as a trade-off.

Table 14: Pareto Frontier: Trade-off Between Profit and Sugar Content (Heterogeneous Harvest Window, Heterogeneous Plot Size).

#	Profit ($)	Sugar (tons)
1	612,414.46	2,775.20
2	609,761.71	2,778.61
3	609,761.71	2,780.32
4	607,023.06	2,783.73
5	603,729.46	2,785.44
6	603,625.29	2,787.14
7	601,438.27	2,788.85
8	599,977.80	2,790.56
9	596,329.16	2,793.97
10	592,446.28	2,795.67
11	591,522.25	2,797.38
12	584,429.69	2,799.09
13	579,497.26	2,800.79
14	573,347.51	2,802.50
15	562,017.04	2,804.20
16	544,270.76	2,805.91
17	504,933.86	2,807.62

Table 15: Comparison of Max Profit and Max Sugar Content Solutions: Base vs Heterogeneous Instance.

Solution	**Instance**	**Mill 1 Assign.**	**Mill 2 Assign.**	**Disposals (# plots)**
Max Profit	Base	62/65 plots	3/65 plots	0
Max Profit	Heterogeneous	59/65 plots	6/65 plots	0
Max Sugar	Base	52/65 plots	13/65 plots	7
Max Sugar	Heterogeneous	45/65 plots	20/65 plots	7

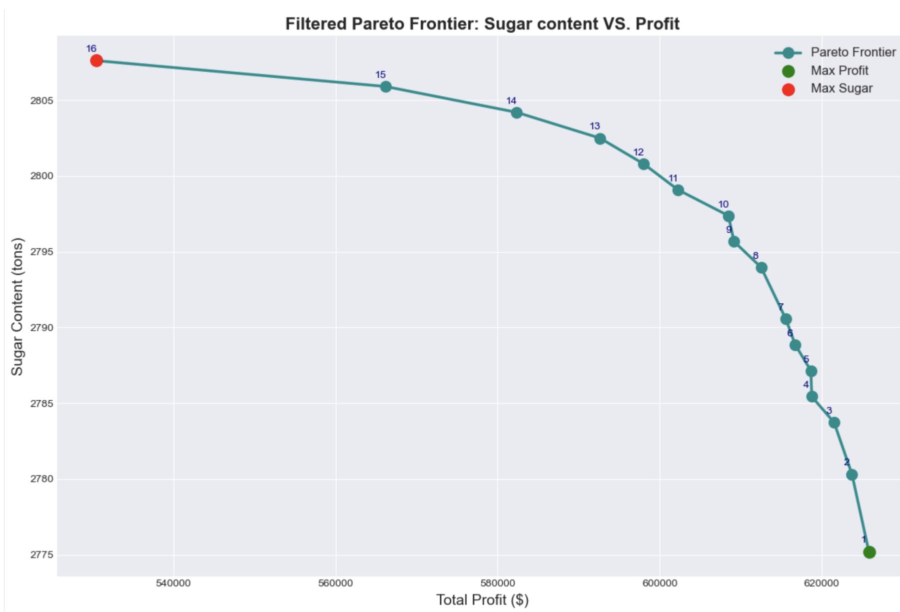

Figure 7: Pareto Frontier of heterogeneous harvest window and plot size.

5.3.2 Capacity Utilization and Operational Bottlenecks

A comparison of capacity utilization between the base and heterogeneous instances under the maximum sugar content objective reveals both stable patterns and meaningful differences driven by increased heterogeneity. In both cases, harvesting and processing activities are highly synchronized with mill and transport capacities.

In the base instance, capacity usage is more variable. Mill 1 typically handles the majority of harvest and processing load, with an average utilization of about 58% for harvesting and 60% for processing, in Table 17. Mill 2, on the other hand, sees far more uneven usage, with average harvesting utilization around 29% and frequent periods of zero activity. However, when Mill 2 is used, it often hits the binding (100%) processing capacity, indicating that sugarcane is allocated to Mill 2 primarily when it is absolutely necessary to satisfy the sugar-maximization goal. Vehicle utilization patterns are similarly uneven, with frequent periods of zero usage, particularly for Mill 2.

In contrast, the heterogeneous instance leads to a more balanced operational pattern. Based on Table 17, average utilization rates increase for both mills: harvesting averages rise to roughly 60% (Mill 1) and 43% (Mill 2), while processing averages reach 63% (Mill 1) and 58% (Mill 2). The periods of zero utilization decrease, reflecting a more consistent workload for all resources. The frequency of binding (100%) utilization at Mill 2 remains similar, underscoring its role as a bottleneck for high-sugar solutions, but overall, the loads are distributed more evenly across time and facilities.

These shifts are a direct consequence of introducing variability into harvest windows and plot sizes, which forces the model to smooth activities across available periods and resources. The operational result is a less concentrated and more resilient use of capacity, potentially reducing idle time and improving fleet and mill efficiency.

Table 17: Summary of Capacity Utilization Under Max Sugar Content Solution.

Metric	Base Instance		Heterogeneous Instance	
	Mill 1	Mill 2	Mill 1	Mill 2
Avg. Harvest Utilization (%)	57.8	29.2	59.6	42.8
Max Harvest Utilization (%)	85.3	100.0	74.4	100.0
Periods at Binding (100%)	0	7	0	7
Avg. Processing Utilization (%)	60.5	39.6	63.0	58.2
Max Processing Utilization (%)	85.3	100.0	74.4	100.0
Avg. Vehicle Utilization (%)	36.7	25.1	38.8	29.6
Periods of Zero Utilization (#)	12	17	8	10

Note: "Avg." denotes the average across all periods; "Max" is the highest single-period utilization. "Periods at Binding" counts periods when capacity is fully used. All numbers are based on the specific max sugar solution for each scenario.

5.4 Robustness check of base model on multiple instances

To evaluate the stability of the base multi-objective optimization model and assess the sensitivity of results to variability in initial harvesting schedules, a robustness analysis was conducted by generating 10 random instances of the base model. Each instance used the same structural formulation and parameter values but differed in the randomly assigned harvest window for each plot, shown in Appendix A. This procedure accounts for potential variability in operational timing by incorporating such factors into the instance generation. While the optimization model itself remains deterministic, these variations in the input data allow the analysis to reflect realistic operational variability. For each instance, both the profit-maximizing and sugar-maximizing solutions were obtained, and the complete Pareto frontier between the two objectives was computed. The aggregated results were then compared to assess consistency in performance metrics and trade-off structures.

5.4.1 Summary of Extreme Solutions

Across the 10 instances, the profit-maximizing solutions yielded a mean profit of \$557,459.28 with a standard deviation of \$12,021.11, and a range from \$546,542.01 to \$577,613.87. The corresponding sugar outputs averaged 2,740.29 tons (std: 13.89 tons), with a range of 2,712.99 tons to 2,752.33 tons, show in Table 18.

In contrast, the sugar-maximizing solutions achieved an average sugar output of 2,778.11 tons (std = 0.98 tons), representing an average increase of 1.38% relative to the profit-maximizing case. However, this gain in the sucrose yield came at an economic cost: the mean profit declined to \$456,054.94 (std = \$17,275.60), corresponding to a reduction of 18.2% in profit, with the decrease ranging between 12.1% and 20.6% across all instances (Table 19).

This stability indicates that the observed trade-offs between revenue and sucrose yield are robust to such operational variability.

Table 18: Per-instance comparison: Max Profit vs. Max Sugar solutions.

Instance	MaxProfit_Profit	MaxProfit_Sugar	MaxSugar_Profit	MaxSugar_Sugar
1	563,089.10	2,750.31	470,790.71	2,777.72
2	547,693.75	2,712.99	434,485.54	2,776.75
3	550,543.61	2,728.84	433,177.34	2,778.75
4	573,142.28	2,747.69	465,602.89	2,777.36
5	568,921.56	2,750.17	457,365.84	2,778.95
6	547,258.81	2,746.86	462,221.90	2,777.20
7	548,406.65	2,752.33	474,678.84	2,777.52
8	577,613.87	2,745.22	477,505.81	2,779.36
9	546,542.01	2,746.92	433,219.14	2,779.57
10	551,381.19	2,721.59	451,486.17	2,777.97

Table 19: Summary statistics and 95% confidence intervals over 10 instances.

	Summary statistics						95% CI	
Metric	Mean	Std. Dev.	Variance	Min	Max	CV	Lower 95%	Upper 95%
MaxProfit_Profit	557,459.28	12,021.11	144,507,132.78	546,542.01	577,613.87	0.02	550,008.52	564,910.05
MaxProfit_Sugar	2,740.29	13.89	192.81	2,712.99	2,752.33	0.01	2,731.69	2,748.90
MaxSugar_Profit	456,053.42	17,275.60	298,446,286.10	433,177.34	477,505.81	0.04	445,345.89	466,760.95
MaxSugar_Sugar	2,778.11	0.98	0.95	2,776.75	2,779.57	0.00	2,777.51	2,778.72

5.4.2 Aggregated Pareto Frontier

The aggregated Pareto frontier represents the mean trade-off curve between profit and sugar content, obtained by averaging the non-dominated solutions at equivalent positions across all 10 independently generated instances. This averaging approach, rather than focusing on a single run, reduces the influence of instance-specific irregularities and highlights trends that are more representative of the system's general behavior, thereby strengthening the applicability of the results to different field configurations and operational conditions.

For each of 10 instances, we first determine its Pareto end–points: the profit–maximizing solution (shown in Section 3.3), which yields a corresponding sugar level that we treat as the lower bound, and the sugar–maximizing solution as the upper bound. We then generate N_{points} evenly spaced sugar thresholds between these bounds and solve the ϵ–constrained model at each threshold. To align frontiers across instances of different scales, we index points by their relative position:

$$\text{Pos}(k) \;=\; \frac{k-1}{N_{\text{points}}-1}, \qquad k = 1, \dots, N_{\text{points}}.$$

The subtraction by 1 in numerator and denominator anchors k=1 at 0 (the max–profit endpoint) and k=N_{points} at 1 (the max–sugar endpoint), leaving $N_{\text{points}}-1$ equal intervals in between. Averaging solutions at the same k therefore combines equivalent trade–off positions (same percentile along each instance's sugar range), yielding a representative aggregated Pareto curve.

Table 20: Relative positions for $N_{\text{points}} = 20$.

Point index k	Relative position (%)
1	0.00%
2	5.26%
3	10.53%
4	15.79%
5	21.05%
6	26.32%
7	31.58%
8	36.84%
9	42.11%
10	47.37%
11	52.63%
12	57.89%
13	63.16%
14	68.42%
15	73.68%
16	78.95%
17	84.21%
18	89.47%
19	94.74%
20	100.00%

At the profit-maximizing extreme, the average solution yields 2,740.29 tons of sugar with a profit of $557,459.28. Moving along the frontier toward sugar maximization gradually increases sucrose output while reducing profit. At the sugar-maximizing extreme, the average solution reaches 2,778.11 tons of sugar (about 1.38% more than the profit-maximizing case), while profit declines to $456,053.42, representing an average loss of 18.2%, shown in Table 21.

Table 21: Averaged frontier (non-dominated) across all instances.

#	**Sugar (tons)**	**Profit ($)**
1	2,740.29	557,459.28
2	2,746.48	545,153.24
3	2,747.61	544,101.44
4	2,757.97	542,682.18
5	2,759.87	538,470.81
6	2,763.61	533,766.75
7	2,765.41	531,365.01
8	2,767.29	530,425.93
9	2,769.25	526,222.20
10	2,771.15	523,213.22
11	2,772.61	518,496.99
12	2,774.49	509,198.07
13	2,776.37	493,229.27
14	2,778.11	456,053.42

The averaged frontier exhibits the expected concave shape (Figure 8), with a relatively flat profit decline for small sugar gains near the profit-maximizing point, followed by a sharper drop as sugar approaches its maximum. The point of diminishing returns, at approximately 2,766.17 tons of sugar and $530,425.93 profit, offers a balanced compromise where further gains in sugar incur disproportionately large profit losses. The preservation of concave shape, diminishing return region, and trade-off pattern across averaged and individual frontiers confirms that the model produces consistent and stable Pareto structures across different instances.

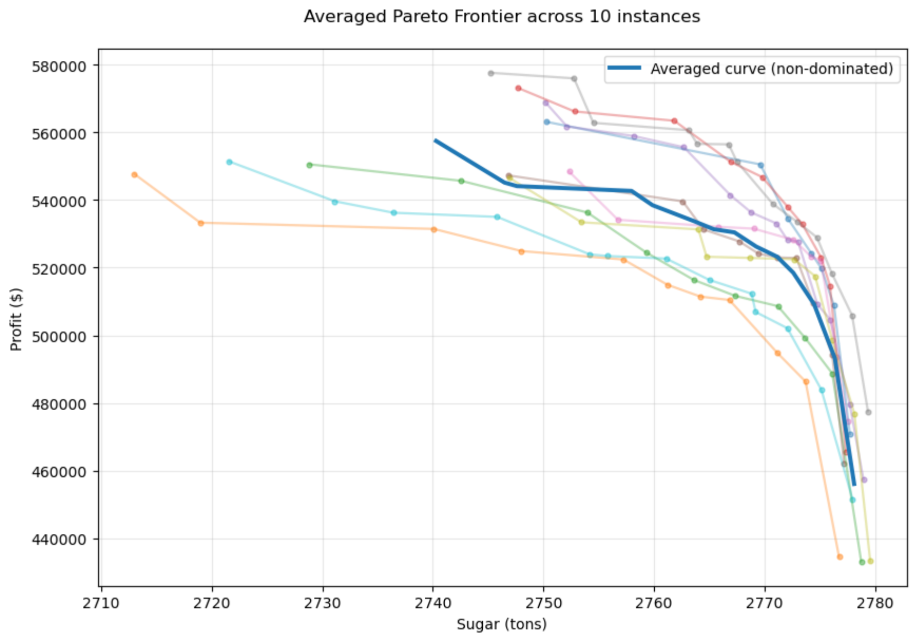

Figure 8: Aggregated Pareto frontier across 10 instances.

Overall, the aggregated Pareto frontier provides a robust and generalizable representation of the trade-off between profit and sugar content. Averaging across 10 independent instances reduces noise from run-specific variability and reveals the central tendency of the optimization outcomes. This consistency across instances highlights the stability of the model and offers decision-makers a clear reference for selecting balanced operational strategies.

6 Parameters sensitivity analysis

Sensitivity analysis is used to test the robustness of a model's conclusions by exploring how changes in assumptions or parameters might influence the results (Goldsmith, 2016). In this chapter, sensitivity analysis is applied to assess the influence of different key parameters on the basic multi-objective optimization model. Specifically, input parameters such as capacities of harvesting machines, cost units and selling prices over the planning horizon are varied within predefined ranges. Then, the results of the sensitivity analysis are compared with those of the base model.

6.1 Parameters Tested

The parameters selected for the sensitivity analysis, along with their tested ranges and baseline values, are shown in Table 22. The baseline scenario is aligned with the parameter settings described earlier in the instance description, reflecting representative values from the heterogeneous model. This configuration provides a realistic operational reference point for all subsequent comparisons.

The choice of parameters and ranges is motivated by both operational significance and insights from the baseline results in Chapter 5, where processing capacity was identified as the principal bottleneck. Consequently, the harvesting capacity was selected for testing instead of the transport capacity, as the latter is less sensitive due to the rounding-up effect in vehicle number calculations. Cost parameters (harvesting, processing, and disposal) and the selling price of sugar were included because they directly affect profitability and influence the trade-offs between the harvesting, processing, and disposal decisions. The tested ranges for each parameter were designed to capture realistic variability in market and operational conditions, while also allowing for the detection of threshold effects where system behavior changes abruptly.

Table 22: Parameter Ranges and Baselines Used in Sensitivity Analysis

Parameter	**Description**	**Tested Values**	**Baseline**
Harvesting capacity per period CAP_i^{harv}	Maximum cane harvested per period	[500, 1,100] (increments of 100 t)	850 t/period
Harvesting cost C_i^{harv}	Cost to harvest one tonne of cane	[0, 80] (increments of $10, same for both mills)	Mill 1:$13.33/t; Mill 2:$15.67/t
Processing cost C_i^{proc}	Cost to process one tonne of cane	[40, 100] (increments of $10, same for both mills)	Mill 1:$40/t; Mill 2: $55/t
Disposal cost C_i^{disp}	Net cost or subsidy for disposing one tonne of cane	[-60, 10] (increments of $5, same for both mills)	$0/t
Selling price P^{sell}	Revenue per tonne of sugar	[300, 1,500] (increments of $150)	$650/t

In the sensitivity analysis, each parameter is varied independently across its range while all others remain fixed at baseline. For every such parameter setting, the full optimization model is solved to maximize total profit and get the sugar content under the maximize profit solution, with the resulting solution structure comprehensively extracted and recorded. This includes not only main performance metrics such as maximum attainable profit and total sugar produced at optimal profit, but also detailed measures such as the marginal or average profit per ton of cane and sugar. In addition, the plot-level assignments for harvest and processing, as well as the quantities and assignments for any disposal, are all systematically output. The analysis also tracks abrupt changes in structure, such as sudden changes in harvested plots or disposal patterns, to pinpoint the operational thresholds where optimal strategies fundamentally change.

When such breakpoints are identified, typically indicated by sudden drops in profit, stepwise losses in sugar output, or shifts in which plots are harvested or disposed, the corresponding solutions are compared in detail. By systematically applying this approach, the analysis provides an insight of how each operational or market parameter influences the optimal strategy, as well as a clear identification of the points at which system behavior fundamentally shifts.

6.2 Harvesting capacity

In this subsection, we vary the per-period harvesting capacity parameter, $CAP_i^{harv} \in [500, 1100]$ tons per period. The resulting solution in Table 23 reveals a clear, non-linear relationship between per-period harvesting capacity and both total sugar content under maximum profit solution and total profit, with a computation time of 17.48 seconds.

Table 23: Sensitivity of Max Profit and Sugar Content to Harvesting Capacity

Harvest Capacity	**Max Profit ($)**	**Sugar At Max Profit (t)**
500	428,999.46	2,721.10
600	537,735.71	2,725.58
700	592,416.84	2,757.68
800	602,293.17	2,750.07
900	619,643.02	2,790.20
1,000	625,688.82	2,803.80
1,100	625,688.82	2,803.80

As presented in Figure 9 and 10, both curves climb steeply from 500 tons to roughly 900 tons. Sugar content increases from 2,721 tons at 500 tons capacity to 2,790 tons at 900 tons capacity, and profit rises from \$429k to \$619k. This increasing phase demonstrates that harvesting capacity is a binding constraint, indicating that every additional ton admitted is fully processed, boosting both total sugar content and total profit. Beyond a harvesting capacity of about 1,000 tons/period, however, both sugar (peaking at 2,803 tons) and profit (leveling off at \$625k) flatten. The plateau clearly marks the point at which milling capacity becomes the system bottleneck: additional harvested canes cannot be milled and hence contribute neither to sugar output nor to profit beyond this threshold.

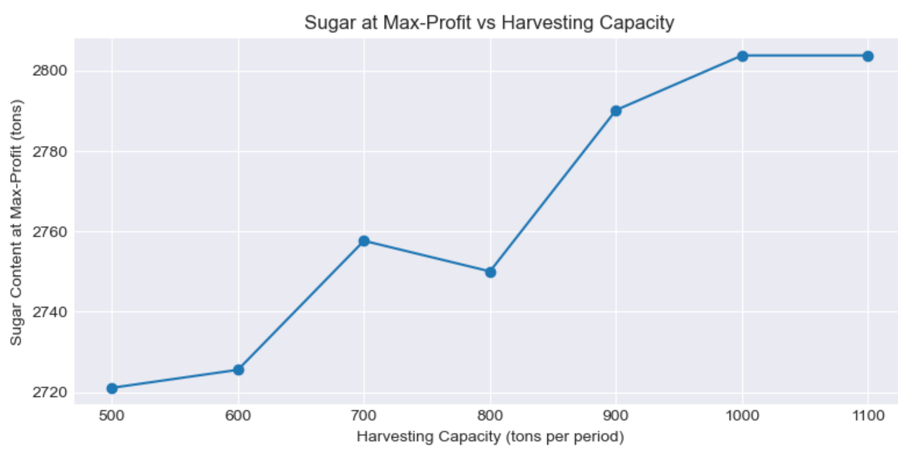

Figure 9: Sensitivity analysis of harvesting capacity to sugar

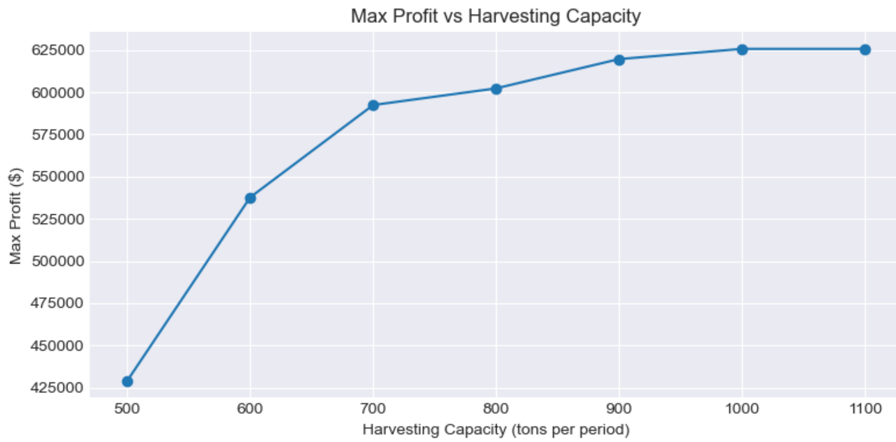

Figure 10: Sensitivity analysis of harvesting capacity to profit

A closer examination of the shift from 700 to 800 tons capacity (Table 24) reveals why sugar output slightly decreases even as profit grows. At 700 tons of harvesting capacity, the model admits only the highest-Pol plots, yielding 2,757.68 tons sugar output and $592.4k profit. Expanding to 800 tons of harvesting capacity increases profit by 1.7% to $602.3k, but sugar falls by 0.3% to 2,750.07 tons. The additional 100 tons at 800 tons capacity comes from lower-Pol fields, which dilutes the overall sugar yield while generating higher unit margins and thus greater profit.

Table 24: Comparison of 700 tons vs. 800 tons Harvesting Capacity Solutions

Metric	**700 t/period**	**800 t/period**
Max. profit ($)	592,416.84	602,293.17
Total sugar (t)	2,757.68	2,750.07
Tons of cane harvested (t)	700	800
Additional cane admitted (t)	–	100
Profit per tonne of cane ($/t)	846.31	752.87
Profit per tonne of sugar ($/t)	214.77	219.08
Primary shift in harvest assignment	Only highest-Pol plots	Adds lower-Pol plots
Net effect on sugar vs. profit	Maximizes sugar	+1.7% profit / –0.3% sugar

6.3 Harvesting cost

In this section, we span the harvesting cost from \$0 to \$80 per ton for both mills. In Table 25, there is a near-linear decrease in profit as costs rise, and the harvested sugar tonnage remains remarkably stable over a wide range of low to moderate harvesting costs, only beginning to fall once the cost passes key breakpoints, within the run time of 23.29 seconds. The almost-linear decline in profit with rising harvest cost reflects the underlying linearity of the objective function. The Figure 11 shows that, each \$10/ton increase in harvesting cost corresponds to an approximately 23% reduction in maximum profit over the whole range. At a critical cost of \$43.1/ton, the project crosses the break-even threshold; beyond this point, profitability becomes negative. The cost-profit relationship remains nearly linear throughout the examined range.

Table 25: Sensitivity of Maximum Profit to Harvesting Cost

Harvest Cost ($/ton)	**Max Profit** ($)	**Sugar Content** (tons)
0.0	887,158.56	2,775.68
10.0	681,037.65	2,775.68
20.0	474,970.22	2,775.14
30.0	269,181.47	2,771.93
40.0	63,439.04	2,771.93
43.1	0.00	2,771.93
50.0	-142,303.40	2,771.93
60.0	-347,958.07	2,763.57
70.0	-553,003.99	2,760.10
80.0	-758,006.28	2,760.10

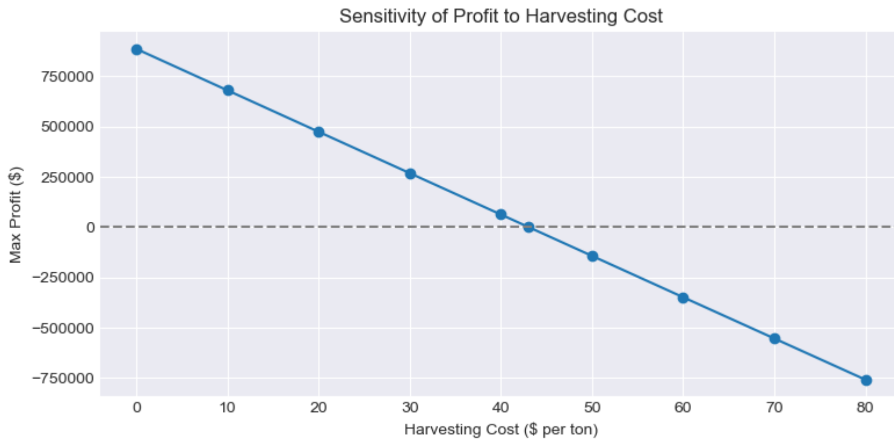

Figure 11: Sensitivity analysis of harvesting cost to profit

The sensitivity of the total sugar yield to the rising harvest costs is characterized by a distinct stepwise pattern. Specifically, the model maintains a constant output of 2,775.68 tons at \$0 and \$10/ton, falls only marginally to 2,775.14 tons at \$20, then steps down to 2,71.93 tons from \$30 to \$50, before further discrete reductions to 2,763.57 tons at \$60 and 2,760.10 tons at \$70 and \$80, according to Figure 12. These plateaus arise from the all-or-none constraint of harvesting decisions: until a cost threshold is crossed, high-sugar plots remain profitable and so sugar yield is inelastic to cost increases; as costs increase, once the harvest cost of the least profitable remaining plot exceeds its revenue potential, the model continues to harvest and transport the cane to the mill, but it is not processed and thus contributes nothing to sugar output (to satisfy harvest scheduling constraints). This unprocessed cane is effectively wasted from a sugar-production perspective, leading to a discrete drop in total sugar. Thus, the piecewise-constant sugar curve directly reflects the underlying integer optimization structure and the sequential exclusion of lower-yield plots as harvesting becomes more expensive.

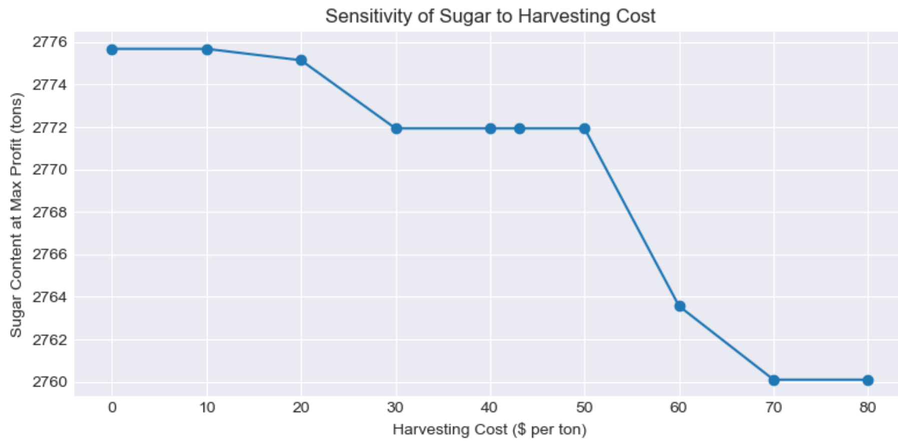

Figure 12: Sensitivity analysis of harvesting cost to sugar

6.4 Processing cost

In this section, we test the sensitivity of processing cost, by changing it between 40 and 100 at the same time for both mills, within the run time of 15.82 seconds. When processing cost increases, maximum profit declines in an almost-linear style in Table 26, indicating the trend observed under harvesting cost sensitivity. As processing cost rises from \$40/t to \$100/t for both mills simultaneously, profit falls with a near-constant slope of 69.3%, in Figure 13. This near-linear decline underscores the dominant influence of per-ton processing costs on overall profitability, in the same way that increases in harvesting costs similarly reduce returns.

Table 26: Sensitivity of Max-Profit and Sugar Content to Processing Cost

Proc. Cost ($/t)	Max Profit ($)	Sugar (t)
40	618 469.17	2 797.33
50	411 851.48	2 796.87
60	205 248.16	2 796.87
70	–1 327.63	2 795.50
80	–207 625.08	2 792.63
90	–351 450.79	2 551.14
100	–351 450.79	2 551.14

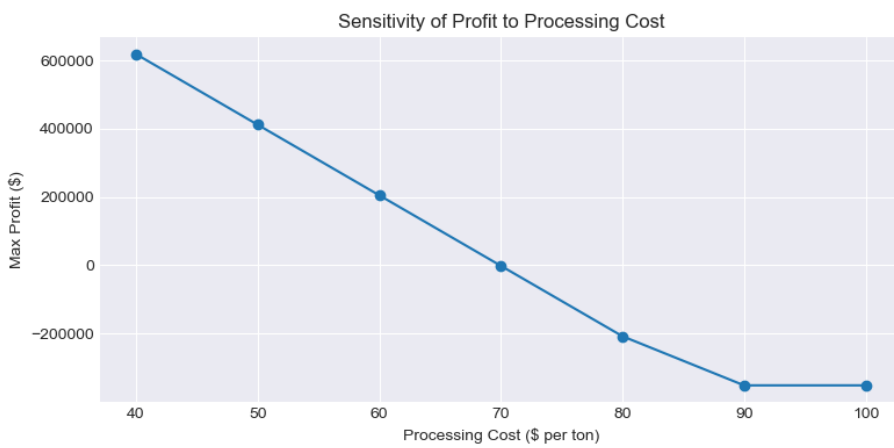

Figure 13: Sensitivity analysis of profit to processing cost

Sugar output, by contrast, remains remarkably inelastic for moderate cost inflation, based on Figure 14: retaining over 99.8% of its baseline (2,797 tons) for processing costs up to $60/t and falling only marginally (to 2,792.6 tons, a 0.16% reduction) at $80/t. Negative profit scenarios emerge once processing costs exceed $70/t, with increasingly steep losses as costs rise.

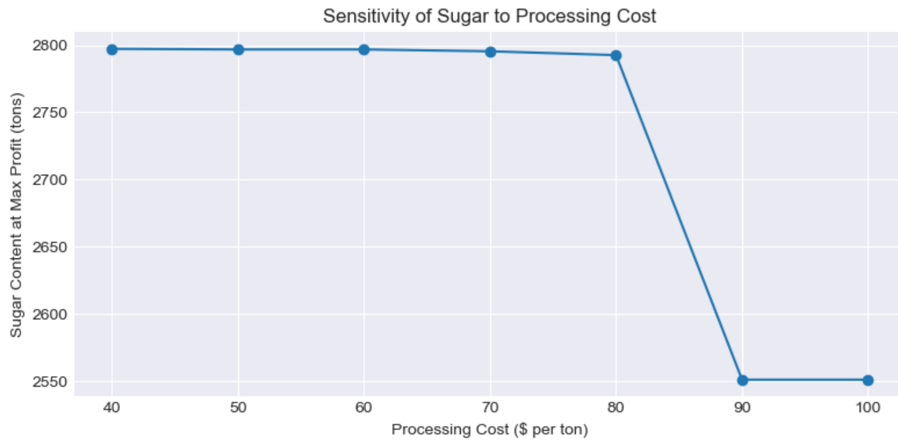

Figure 14: Sensitivity analysis of sugar to processing cost

At $80/t, the operation still processes the cane from all the plots, resulting in a modest negative margin of –$74.42/t but maintaining throughput at 2,792.6 tons. However, the critical threshold is reached at $90/t: here, two low-yield plots become uneconomical to process. While these plots are still harvested, their cane is fully disposed of rather than milled. This selective abandonment reduces sugar production by 241.5 tons (–8.65%) and worsens the margin to –$137.75/t, pushing total losses to –$351,451 (Table 27). The $100/t scenario repeats these outcomes, confirming that the decision change occurs precisely at the $90/t breakpoint. The abrupt drop between $80/t and $90/t in Figure 14 marks the model's structural shift: the optimizer excludes marginal plots to reduce processing losses, sacrificing volume to improve unit economics under high-cost conditions.

Table 27: Comparison of Solutions at Processing Costs of \$80/t vs. \$90/t

Metric	\$80/t	\$90/t
Max. profit (\$)	–207 625.08	–351 450.79
Sugar produced (t)	2 792.63	2 551.14
Profit per tonne of sugar (\$/t)	–74.42	–137.75
Percentage change in profit	—	–69.3%
Percentage change in sugar	—	–8.65%
Primary shift in processing decision	All plots remain profitable	Two marginal low-yield plots abandoned
Net effect on sugar vs. profit	Moderate throughput loss, moderate loss	Severe throughput reduction, large loss

6.5 Disposal cost

This section examines the sensitivity of the optimal harvesting and processing decisions by changing the disposal cost, varying from a significant revenue (-\$60/t, representing a payment or subsidy received per ton disposed for alternative uses such as ethanol production or other by-products) to moderate disposal expense (\$10/t, assuming that the mill must pay to dispose of any excess cane over the offsetting revenue, such as land-filling, composting, or other waste management options). Here, negative disposal costs represent not only subsidies for waste removal, but also the net economic gain from utilizing residues into co-products such as ethanol, bio-energy, or animal feed. Positive disposal costs reflect situations where the mill must pay to remove surplus cane (e.g., landfill, composting, or other waste management). In this scenario, disposal becomes a financial penalty rather than a potential source of income. When disposal provides high returns (large negative values), the optimizer actively disposes of lower-quality or excess cane to capture this revenue, prioritizing high-POL plots for processing. As disposal becomes less lucrative and then costly, the model increasingly favors processing all available cane to avoid penalties, even if that means harvesting at sub-optimal sugar maturity.

Across this wide cost range, the maximum achievable profit decreases monotonically and exhibits a piecewise-linear trend within the run time of 39.32

seconds (Figure 15). Specifically, in Table 28, at highly negative disposal costs (-$60/t), the profit reaches its peak ($872,101), since disposing of excess or lower-quality sugarcane yields additional revenue. As the disposal cost increases (less negative or more positive), profitability gradually declines and stabilizes from -$40/t onward at a minimum profit of $612,414. Sugar production displays minimal variability initially, remaining relatively stable between -$55 and -$50/t (around 2,781 tons), but exhibits fluctuations between -$45/t and $-40/t, indicating shifts in harvesting and disposal strategies (Figure 16).

Because solution structures are identical across most intermediate values, Table 28 lists only points where changes occur. For example, between –$55 and –$50/t, the harvest/disposal assignment is identical; profit changes solely because of the lower subsidy rate. In addition, the maximum profit and sugar output keep the same, starting from -$40/t of disposal cost.

Table 28: Sensitivity of Maximum Profit and Sugar Content to Disposal Cost

Disposal Cost ($/ton)	**Max Profit ($)**	**Sugar at Max Profit (t)**
-60	872,100.57	2,789.26
-50	664,748.72	2,781.91
-45	614,129.84	2,786.55
-40	612,414.46	2,775.20
-20	612,414.46	2,775.20
0	612,414.46	2,775.20
10	612,414.46	2,775.20

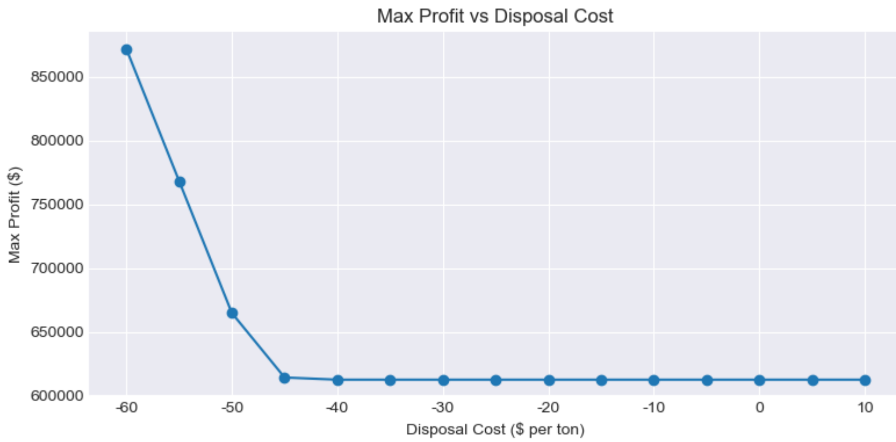

Figure 15: Sensitivity analysis of disposal cost to profit

Comparing the detailed solutions at disposal costs of -$55/t and -$50/t, an identical harvesting and disposal assignment is observed. Although the total profits differ notably (declining from $768,391 to $664,749 only due to the lower disposal subsidy), the sugar yield remains constant at 2,781.91 tons. This consistency arises because both disposal costs lie within the same sensitivity range, where the optimal solution maintains its structure. Therefore, the solution retains the same plots allocated for disposal, resulting in no change in harvested sugarcane or total sugar produced.

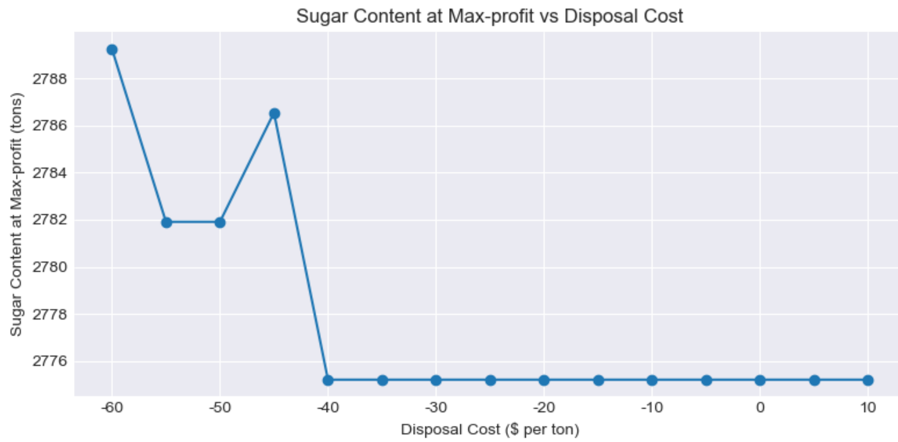

Figure 16: Sensitivity analysis of disposal cost to sugar

A distinct shift occurs at a disposal cost of -$45/t, where the total sugar yield unexpectedly increases slightly to 2,786.55 tons. This rise in sugar production occurs because the increased disposal cost now incentivizes processing over disposal for certain borderline-quality plots. Specifically, several previously disposed plots are reallocated for processing due to reduced profitability in disposal. Consequently, the harvested tonnage that was previously discarded now contributes to additional sugar yield, optimizing overall performance at this specific disposal cost.

This transition between -$50 and -$45/t is driven by the increased penalty associated with disposal, shown in Table 29: as the cost of disposing cane rises, it surpasses the marginal processing profit for borderline plots (specifically, plots 2, 10, 21, 35, and 65). Consequently, the model reallocates these plots for harvest at their earliest feasible periods to maximize sugar before maturity declines further. This adjustment results in all plots being processed, leading to a modest but notable increase in total sugar yield (from 2,781.91 to 2,786.55 tons, a 0.17% gain), despite an overall reduction in profit (−7.6%), due to higher associated costs. The underlying reason is a shift in the economic trade-off: as disposal becomes less attractive, the optimizer broadens its selection criteria, moving from a selective processing strategy where only high-value plots are accepted, to a more inclusive strategy that captures the marginal value of previously abandoned plots. This dynamic highlights how the disposal policy directly influences the extent of resource utilization and sugarcane throughput in the system.

Table 29: Comparison of Decisions under Two Disposal-Cost Scenarios

Metric	**Disposal Cost = –50**	**Disposal Cost = –45**	**Difference / Explanation**
Max. profit ($)	664,748.72	614,129.84	–7.6% decreases as disposal becomes more expensive
Max. sugar produced under Max. profit (t)	2,781.91	2,786.55	+0.17% increase as more cane is processed
Plots originally disposed	2, 10, 21, 35, 65	None	All previously disposed plots are now harvested and processed
Plots newly processed	—	2, 10, 21, 35, 65	These five plots switch from disposal to being harvested and processed
Harvest and milling time for switched plots	Not harvested	All at earliest feasible period	Model shifts to earliest feasible harvest to capture sugar before maturity loss
Processing decisions	Lower throughput (less cane processed)	Higher throughput (more cane processed)	Switched plots contribute to increased processing
Total cane processed	Lower	Higher	Inclusion of switched plots increases total throughput
Rationale for change	Disposal cost not punitive enough; borderline plots disposed	Higher disposal cost makes disposal less attractive; processing threshold crossed	As disposal becomes less lucrative, processing is now the optimal economic choice for this plot
General trend	More selective, only high-value plots processed	Broader inclusion, more plots accepted	Model becomes less selective as disposal cost increases

At a disposal cost of -\$40/t, the system enters a regime where the profit plateaus at its lowest observed value of \$612,414, following a sharp decline from the previous threshold at -\$45/t. Although disposal costs continue to increase, the model's ability to further reduce actual disposal events is almost impossible, since almost all plots are already being processed rather than disposed of. As a result, any additional increases in disposal cost do not result in new gains in throughput or resource utilization. Instead, the model must adjust harvest timing more aggressively, shifting plots to earlier or later periods, often at the expense of optimal sucrose maturity. This results in only marginal reductions in sugar yield (from 2,786.55 to 2,775.20 tons, a 0.4% decrease), but the overall profit remains depressed because higher operational and processing costs cannot be offset by increased sugar revenue. In effect, profit remains at its lowest value, because the system can no longer change which plots to dispose of or process. All the things left is to make less efficient timing decisions, which cannot compensate for the now-high disposal penalties. This also causes a small drop in sugar yield, as plots are not always harvested at the best time.

In conclusion, varying disposal costs drive significant changes in the optimal sugarcane harvest and processing strategy, particularly at specific threshold points. While highly negative disposal costs incentivize aggressive disposal to maximize revenue, increasing costs shift the strategy toward greater processing, influencing harvest timing and plot assignments, and thereby affecting both profit and sugar yield.

6.6 Selling price

The sensitivity analysis of the max-profit solution relative to the selling price demonstrates a distinct shift in system behavior as the price increases. In Table 30, under the run time of 24.53 seconds, when the selling price is below approximately \$600 per ton, profit remains low or even negative (–\$349,886 at \$300/t), as the revenue generated is insufficient to cover the costs of processing. In this range, only a small fraction of the available sugarcane is processed, or in some cases, the system may choose not to process any cane at all even though it has been harvested, resulting in a restrained sugar output (2,587.5 tons at $300/t).

Table 30: Sensitivity of Maximum Profit and Sugar Content to Selling Price

Sell Price ($/t)	**Max Profit ($)**	**Sugar at Max Profit (t)**
300	–349,886.40	2,587.47
450	57,767.38	2,771.93
600	473,654.40	2,775.20
750	889,967.20	2,775.68
900	1 306,319.00	2,775.68
1050	1 722,670.00	2,775.68
1200	2 139,273.00	2,775.68
1350	2 556,429.00	2,781.12
1500	2 973,598.00	2,781.12

Figure 17: Sensitivity analysis of selling price to profit

Once the selling price surpasses the break-even point (around $600 per ton in this scenario), profit transitions to a linear increase with respect to the selling price. Above this threshold, all feasible plots are harvested and processed to maximize throughput. For example, when the selling price is raised to $750/t, profit rises sharply to $889,967, and remains proportional to further increases (till $2,973,598 at $1,500/t), shown in Figure 18. In this upper regime, the total sugar produced stabilizes around 2,775 to 2,781 tons, indicating that all available capacity is being utilized.

Figure 18: Sensitivity analysis of selling price to sugar

In summary, profit increases approximately linearly with selling price across the full range. At low price levels, the system engages in selective processing of only the most profitable cane. However, once the selling price exceeds the break-even threshold, profit rises more steeply as the model fully utilizes all available sugarcane resources. This pattern highlights the critical role of market price in unlocking the supply chain's productive capacity and optimizing profit.

6.7 Processing window

The processing window, which defines the permissible lag between sugarcane harvest and processing, is a key operational constraint in sugarcane supply chain management. In many real-world systems, sugarcane is ideally processed immediately after harvest to minimize sucrose loss, often by enforcing a just-in-time (JIT) inventory policy, which requires that all harvested canes are crushed within the same period. However, the strict JIT operation strategy may limit the system's flexibility and hinder the ability to optimize sugar output, particularly under fluctuating field and factory conditions. To investigate the impact of increased operational flexibility, we relax the processing window constraint, allowing harvested sugarcane to be stored for up to one additional period before processing. This adjustment more closely reflects real-world scenarios where limited in-plant inventory is available and can address short-term mismatches between harvesting and milling schedules.

6.7.1 New sets and parameters

In the expanded processing window scenario, we introduce updated sets and parameters to reflect the operational realities of short-term inventory in sugarcane milling. Most notably, we define the set $P_{hj} = \{h, h+1\}$, subject to the overall planning horizon, which specifies the set of feasible processing periods for each plot j harvested in period h. This adjustment allows harvested cane to be processed either immediately or within one additional period, thereby capturing the operational benefit of limited buffer storage while still prioritizing rapid throughput.

To enforce this buffer, we assign a strict inventory capacity to each mill: $CAP_1^{inv} = 175$ tons and $CAP_2^{inv} = 100$ tons, shown in Table 31. These values are purposely kept low, underlining industrial practice, where perishable crops like sugarcane are rarely stored in large quantities due to rapid quality deterioration and logistical constraints. In conjunction with the new inventory allowance, an inventory holding cost is applied at a rate of $C_1^{inv} = C_2^{inv} = \$1$ per ton per period. This value is selected, because holding costs of perishable products typically represent less than 10% of the product price. Together, these parameters realistically constrain the system to maintain just-in-time flow, while granting the flexibility needed to optimize processing and harvest synchronization.

Table 31: Inventory-Related Parameters for Relaxed Processing Window

	Inventory Capacity (CAP_i^{inv}, t)	Inventory Cost (C_i^{inv}, \$/t/period)
Mill 1	175	1
Mill 2	100	1

6.7.2 Result analysis

Allowing a more relaxed processing window, permitting harvested sugarcane to be stored and processed in the subsequent period, rather than requiring immediate just-in-time processing, yields significant benefits for sugar maximization, while leaving the maximum profit solution essentially unchanged. This modification fundamentally alters the system's operational dynamics, as reflected in the changes in disposal volumes, the multi-period processing patterns, and the endpoint performance of the Pareto frontier.

The most striking finding is that both the maximum achievable profit and the absolute maximum sugar output remain unchanged between the two models, with values plateauing at $612,414.46 and 2,807.62 tons, respectively. This indicates that, under both configurations, the system already fully utilizes the critical capacity and resource constraints. Thus, allowing a modest degree of inventory does not expand the absolute production frontier, as the bottlenecks imposed by milling or harvest capacity are already binding at the optimum.

However, the structure of the solutions at the endpoint of the Pareto frontier does differ. In the relaxed processing window scenario, the profit at the maximum-sugar point is higher ($517,509.97 compared to $504,933.86 in the heterogeneous case). This gain reflects improved operational flexibility: by allowing one-period delay before processing, the model can schedule harvests and mill operations in a way that achieves the same sugar yield but at lower overall cost, by reducing idle capacity, avoiding unnecessary disposals, and smoothing processing loads. As a result, the solution at the maximum sugar endpoint becomes more profitable, reflecting the optimizer's ability to sequence and batch process cane more efficiently across time.

Operationally, the looser processing window leads to a marked reduction in both the number of plots requiring disposal and the total volume of cane disposed at the sugar-maximizing solution. The heterogeneous model necessitates disposal from seven plots, totaling 561.29 tons, whereas the relaxed-window configuration reduces this to only three plots and 125.8 tons. This improvement reflects greater system flexibility: cane from marginal plots that would otherwise be discarded due to temporal or capacity conflicts can now be stored and processed in the subsequent period.

Table 32: Comparison of Base and Looser Processing Window

Metric	Base Alternative Model	Looser Processing Window	Change / Commentary
Operational structure	Just-in-time only	Inventory allowed for 1 period	More flexible
Max. profit ($)	612,414.46	612,414.46	No change (plateau reached)
Max. sugar at max profit (t)	2,775.20	2,775.20	No change
Max. sugar (t)	2,807.62	2,807.62	No change (plateau reached)
Max. profit at max sugar ($)	504,933.86	517,509.97	Higher profit possible at max-sugar solution
Sugar increase at same profit level	–	+2–5 tons	Slightly higher
Disposals at max sugar	7 plots disposed: 2, 18, 32, 42, 56, 61, 62	3 plots disposed: 32, 61, 62	
Total disposed cane at max sugar (t)	561.29	125.8	
Plots processed over multiple periods	No	Yes (plot 2, 4, 14, 18, 21, 54, 62)	

In summary, allowing a one-period processing window does not extend the system's absolute profit or sugar yield, but it significantly improves operational efficiency at key points along the Pareto frontier. By allowing for strategic storage and phased processing, the model achieves higher profit at the sugar-maximizing endpoint and reduces both the volume and number of disposals, meaning that benefits underscore the value of even modest inventory flexibility in highly constrained agricultural supply chains.

7 Conclusion

7.1 Conclusions

This study developed and analyzed a detailed multi-objective optimization model for the sugarcane supply chain, integrating harvest scheduling, processing allocation, and disposal decisions at the plot level, while also capturing the dynamic interaction between harvested tonnage and sucrose content over time. By combining operational constraints including harvesting, transportation and milling capacities, time windows, and plot heterogeneity, with economic drivers such as costs, selling prices, and disposal penalties, the model provides a robust framework for evaluating real-world management trade-offs, upon the existing literature on agricultural supply chain optimization. From the literature review, the study identified that while many previous works address isolated stages of the sugarcane chain (for example, harvest scheduling, transportation routing, or processing), few integrate them into a single multi-objective framework capable of capturing profit–sugar trade-offs, by embedding both tonnage and sucrose dynamics.

The mixed integer programming model (MIP) developed here incorporates harvesting window and plot size heterogeneity, dynamics of sucrose over time, and capacity limits across harvesting, transportation, and milling, while optimizing for both profit and sugar output. Application to two types of instances, a base instance with solely randomized harvesting windows and a heterogeneous case combined with randomized plot sizes and harvest window at the same time, enabled examination of how variability in the field alters operational bottlenecks and attainable performance. Analysis of Pareto frontiers for each scenario revealed stable concave trade-off curves between profit and sugar content, with clear efficient regions where modest profit sacrifices yield substantial sugar output gains. Robustness checks confirmed that these patterns and threshold behaviors persist under stochastic variation in plot attributes.

A key contribution of this work is the systematic exploration of parameter sensitivities. By varying harvesting capacities, the analysis demonstrates how physical system bottlenecks shape the attainable frontier between profit and sugar content. Profit and sugar output increase sharply with rising capacity, but plateau once the more restrictive resource (bottleneck) is reached, highlighting the necessity for balanced investments across the supply chain. Disposal cost emerged as one of the most influential levers. When disposal incurs a penalty, the model prioritizes resource utilization, maximizing processed cane and minimizing waste, even if this means accepting a lower overall average sugar content. Conversely, when disposal is subsidized or low-cost, selective processing becomes optimal, with marginal plots being excluded to maximize per-unit profitability.

Another major finding concerns inventory and timing flexibility. Allowing a relaxation of the processing window, permitting harvested cane to be stored and processed in the subsequent period, demonstrates that even modest inventory capacity can significantly increase operational flexibility. While the absolute maximum profit and sugar yield remain unchanged, the system achieves higher profits at the high-sugar solutions, and waste (disposal) is substantially reduced. These results suggest that limited storage investments can yield notable benefits, particularly for supply chains managing highly perishable products under variable field and mill constraints.

The model also uncovers the interaction between market conditions and operational strategy. Sensitivity analysis with respect to the selling price illustrates a pronounced regime change at the break-even threshold, above which the system fully utilizes all available capacity. Below this point, selective harvesting dominates, and both profit and sugar yield remain suboptimal. This reinforces the importance of market intelligence and adaptive planning to capture value in volatile price environments.

In summary, this research advances the state of knowledge in sugarcane supply chain optimization by providing a comprehensive, scenario-driven analysis of operational and economic situation. The results offer clear guidance for practitioners: balanced capacity expansion, targeted waste policy, modest inventory flexibility, and responsive planning are all critical to achieving both economic and production objectives in complex, perishable supply chains.

7.2 Limitations and future research

Despite providing a structured framework for sugarcane harvest and processing optimization, the present study is subject to several important limitations. First, the modeling of sucrose accumulation, post-harvest deterioration, and yield progression is based on linear approximations. In reality, sugarcane growth and maturation are governed by complex, non-linear biological processes, often better captured by sigmoid, polynomial, or logistic functions that account for dynamic changes in physiological development. Environmental variability, including temperature fluctuations, rainfall patterns, soil fertility, and pest pressures, can induce significant deviations from the assumed deterministic growth trajectories. As such, the use of simple linear functions, while enhancing tractability and interpretability, inevitably sacrifices accuracy, especially when extrapolating beyond average-case scenarios.

One promising direction for future work is to incorporate the concept of thermal time or growing degree days (GDD) into the modeling of growth and post-harvest deterioration. Degree day accumulation integrates the effect of temperature over time by summing daily deviations above a base threshold, providing a biologically meaningful measure of crop development. In sugarcane systems, Lofton et al. (2012) demonstrated that cumulative GDD, when combined with normalized difference vegetation index (NDVI), substantially improves the accuracy of yield predictions, highlighting its value as a predictor of physiological progress. Similarly, Han et al. (2022) used GDD as a key input in data-driven early- to mid-season forecasting models, showing that thermal time enhances the reliability of predictions compared with calendar-based metrics. More recently, Dimov et al. (2022) emphasized the importance of integrating temperature-driven variables such as GDD into remote sensing–based time series approaches for yield estimation, rewarding the role of degree days accumulation in capturing nonlinear responses to environmental conditions. The integration of degree-day driven functions and the current optimization framework, would provide a more robust link between environmental variability and sugarcane performance, ultimately enhancing the realism of harvest and processing optimization models.

Secondly, the current model adopts a deterministic framework, with key parameters such as growth rates, harvesting yields, and operational costs treated as known and fixed throughout the planning horizon. In practice, these parameters are subject to considerable uncertainty arising from unpredictable weather, market price volatility, labor availability, and equipment failures. Although randomization is introduced through variations in harvest windows and plot sizes, the model does not explicitly incorporate probabilistic or scenario-based uncertainty.

Another notable limitation is the focus on a single-product supply chain, with sugar identified as the sole output of the system. However, modern sugarcane processing facilities often pursue integrated bio-refinery concepts, producing multiple co-products such as ethanol, molasses, electricity, or bio-based chemicals. By excluding multi-product planning, the model overlooks important economic trade-offs and process synergies that could significantly influence both operational schedules and overall profitability.

Future research could therefore extend the framework in several directions. First, incorporating multi-product optimization with explicit demand, pricing, and process constraints for co-products, would better reflect the realities of contemporary sugarcane industries. Second, the framework could be enriched by considering alternative cane types, such as energy cane, which has a higher fiber content, greater biomass potential, and increased resistance to pests, while being more adaptable to different soil conditions. Third, the model could integrate variety-specific maturation profiles, since sucrose-rich cane cultivars reach their peak at different periods. Optimizing harvest schedules according to variety-specific maturity would allow mills to align processing with peak sucrose content while also mitigating risk through diversification. Finally, considering the spatial arrangement of different sugarcane varieties in adjacent plots could capture agronomic benefits, such as reducing vulnerability to pests and diseases, thereby linking supply chain optimization to long-term sustainability and resilience in sugarcane production systems.

Furthermore, while this study explores the harvesting and processing stages, it adopts a highly simplified treatment of the transportation stage. The movement of harvested cane from fields to mills is typically subject to constraints related to vehicle capacities, routing, loading and unloading times, and travel distances, all of which impact both the timing and cost structure of the supply chain. By abstracting these complexities, the model may underestimate bottlenecks or inefficiencies that arise in real-world logistics operations. Future research should explicitly model transportation decisions, potentially using vehicle routing or network flow formulations, to achieve more holistic and practical optimization.

Finally, the planning horizon and decisions are limited to a single season and aggregated plot-level schedules. Long-term effects such as field rotation, ratoon management, land preparation, and investment in equipment or infrastructure are not considered, nor are the potential benefits of inter-annual planning or multi-seasonal coordination. Integrating these dimensions would further strengthen the model's strategic value for growers, millers, and supply chain managers.

In summary, while the present model offers useful insights for operational planning, its simplifying assumptions and scope constraints should be recognized. Addressing these limitations in future work will enhance both the realism and applicability of sugarcane supply chain optimization in research and practice.

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Appendix

A: Instances of robustness check

Table 34: Harvest windows (start–end) for three instances. Five plots per row.

Instance 1, Seed 12345				
1: [14, 21]	**2**: [24, 31]	**3**: [1, 8]	**4**: [10, 17]	**5**: [12, 19]
6: [7, 14]	**7**: [9, 16]	**8**: [19, 26]	**9**: [14, 21]	**10**: [6, 13]
11: [12, 19]	**12**: [4, 11]	**13**: [14, 21]	**14**: [9, 16]	**15**: [18, 25]
16: [21, 28]	**17**: [6, 13]	**18**: [20, 27]	**19**: [18, 25]	**20**: [6, 13]
21: [12, 19]	**22**: [24, 31]	**23**: [24, 31]	**24**: [3, 10]	**25**: [17, 24]
26: [24, 31]	**27**: [14, 21]	**28**: [19, 26]	**29**: [17, 24]	**30**: [6, 13]
31: [5, 12]	**32**: [7, 14]	**33**: [24, 31]	**34**: [3, 10]	**35**: [7, 14]
36: [11, 18]	**37**: [11, 18]	**38**: [1, 8]	**39**: [15, 22]	**40**: [11, 18]
41: [1, 8]	**42**: [17, 24]	**43**: [23, 30]	**44**: [24, 31]	**45**: [14, 21]
46: [1, 8]	**47**: [1, 8]	**48**: [22, 29]	**49**: [6, 13]	**50**: [25, 32]
51: [19, 26]	**52**: [6, 13]	**53**: [10, 17]	**54**: [4, 11]	**55**: [21, 28]
56: [14, 21]	**57**: [4, 11]	**58**: [22, 29]	**59**: [19, 26]	**60**: [6, 13]
61: [24, 31]	**62**: [13, 20]	**63**: [8, 15]	**64**: [17, 24]	**65**: [20, 27]
Instance 2, Seed 12346				
1: [15, 22]	**2**: [24, 31]	**3**: [15, 22]	**4**: [13, 20]	**5**: [23, 30]
6: [3, 10]	**7**: [24, 31]	**8**: [8, 15]	**9**: [10, 17]	**10**: [9, 16]
11: [11, 18]	**12**: [19, 26]	**13**: [18, 25]	**14**: [15, 22]	**15**: [22, 29]
16: [9, 16]	**17**: [4, 11]	**18**: [13, 20]	**19**: [18, 25]	**20**: [9, 16]
21: [13, 20]	**22**: [7, 14]	**23**: [9, 16]	**24**: [14, 21]	**25**: [1, 8]

Harvest windows (continued)

26: [8, 15]	**27**: [10, 17]	**28**: [9, 16]	**29**: [13, 20]	**30**: [25, 32]
31: [12, 19]	**32**: [3, 10]	**33**: [7, 14]	**34**: [18, 25]	**35**: [12, 19]
36: [10, 17]	**37**: [11, 18]	**38**: [8, 15]	**39**: [9, 16]	**40**: [10, 17]
41: [17, 24]	**42**: [1, 8]	**43**: [1, 8]	**44**: [3, 10]	**45**: [17, 24]
46: [24, 31]	**47**: [6, 13]	**48**: [7, 14]	**49**: [13, 20]	**50**: [15, 22]
51: [17, 24]	**52**: [20, 27]	**53**: [12, 19]	**54**: [9, 16]	**55**: [4, 11]
56: [14, 21]	**57**: [3, 10]	**58**: [24, 31]	**59**: [6, 13]	**60**: [9, 16]
61: [24, 31]	**62**: [16, 23]	**63**: [24, 31]	**64**: [6, 13]	**65**: [12, 19]

Instance 3, Seed 12347

1: [12, 19]	**2**: [3, 10]	**3**: [16, 23]	**4**: [11, 18]	**5**: [15, 22]
6: [10, 17]	**7**: [22, 29]	**8**: [11, 18]	**9**: [15, 22]	**10**: [14, 21]
11: [1, 8]	**12**: [4, 11]	**13**: [21, 28]	**14**: [21, 28]	**15**: [20, 27]
16: [14, 21]	**17**: [10, 17]	**18**: [6, 13]	**19**: [9, 16]	**20**: [7, 14]
21: [9, 16]	**22**: [22, 29]	**23**: [8, 15]	**24**: [22, 29]	**25**: [24, 31]
26: [7, 14]	**27**: [3, 10]	**28**: [14, 21]	**29**: [3, 10]	**30**: [22, 29]
31: [2, 9]	**32**: [1, 8]	**33**: [8, 15]	**34**: [11, 18]	**35**: [2, 9]
36: [20, 27]	**37**: [22, 29]	**38**: [21, 28]	**39**: [8, 15]	**40**: [4, 11]
41: [14, 21]	**42**: [4, 11]	**43**: [9, 16]	**44**: [14, 21]	**45**: [18, 25]
46: [4, 11]	**47**: [19, 26]	**48**: [7, 14]	**49**: [10, 17]	**50**: [5, 12]
51: [4, 11]	**52**: [21, 28]	**53**: [8, 15]	**54**: [18, 25]	**55**: [3, 10]
56: [18, 25]	**57**: [4, 11]	**58**: [4, 11]	**59**: [11, 18]	**60**: [9, 16]
61: [18, 25]	**62**: [14, 21]	**63**: [19, 26]	**64**: [7, 14]	**65**: [17, 24]

Instance 4, Seed 12348

1: [2, 9]	**2**: [21, 28]	**3**: [25, 32]	**4**: [6, 13]	**5**: [16, 23]
6: [9, 16]	**7**: [14, 21]	**8**: [10, 17]	**9**: [11, 18]	**10**: [22, 29]

Harvest windows (continued)

11: [4, 11]	**12**: [2, 9]	**13**: [20, 27]	**14**: [5, 12]	**15**: [4, 11]
16: [18, 25]	**17**: [18, 25]	**18**: [16, 23]	**19**: [14, 21]	**20**: [4, 11]
21: [7, 14]	**22**: [25, 32]	**23**: [20, 27]	**24**: [14, 21]	**25**: [2, 9]
26: [7, 14]	**27**: [3, 10]	**28**: [18, 25]	**29**: [18, 25]	**30**: [18, 25]
31: [22, 29]	**32**: [9, 16]	**33**: [3, 10]	**34**: [21, 28]	**35**: [2, 9]
36: [5, 12]	**37**: [22, 29]	**38**: [16, 23]	**39**: [8, 15]	**40**: [22, 29]
41: [12, 19]	**42**: [18, 25]	**43**: [3, 10]	**44**: [4, 11]	**45**: [9, 16]
46: [3, 10]	**47**: [1, 8]	**48**: [7, 14]	**49**: [12, 19]	**50**: [11, 18]
51: [17, 24]	**52**: [12, 19]	**53**: [22, 29]	**54**: [14, 21]	**55**: [20, 27]
56: [11, 18]	**57**: [25, 32]	**58**: [2, 9]	**59**: [25, 32]	**60**: [3, 10]
61: [24, 31]	**62**: [14, 21]	**63**: [13, 20]	**64**: [4, 11]	**65**: [4, 11]

Instance 5, Seed 12349

1: [2, 9]	**2**: [2, 9]	**3**: [21, 28]	**4**: [1, 8]	**5**: [11, 18]
6: [25, 32]	**7**: [3, 10]	**8**: [22, 29]	**9**: [25, 32]	**10**: [1, 8]
11: [1, 8]	**12**: [7, 14]	**13**: [3, 10]	**14**: [13, 20]	**15**: [15, 22]
16: [24, 31]	**17**: [5, 12]	**18**: [7, 14]	**19**: [6, 13]	**20**: [6, 13]
21: [21, 28]	**22**: [23, 30]	**23**: [13, 20]	**24**: [4, 11]	**25**: [25, 32]
26: [5, 12]	**27**: [13, 20]	**28**: [19, 26]	**29**: [22, 29]	**30**: [20, 27]
31: [6, 13]	**32**: [22, 29]	**33**: [23, 30]	**34**: [1, 8]	**35**: [17, 24]
36: [9, 16]	**37**: [6, 13]	**38**: [5, 12]	**39**: [1, 8]	**40**: [22, 29]
41: [14, 21]	**42**: [10, 17]	**43**: [21, 28]	**44**: [2, 9]	**45**: [8, 15]
46: [6, 13]	**47**: [16, 23]	**48**: [18, 25]	**49**: [5, 12]	**50**: [14, 21]
51: [18, 25]	**52**: [18, 25]	**53**: [13, 20]	**54**: [19, 26]	**55**: [22, 29]
56: [2, 9]	**57**: [22, 29]	**58**: [19, 26]	**59**: [20, 27]	**60**: [21, 28]
61: [24, 31]	**62**: [15, 22]	**63**: [19, 26]	**64**: [20, 27]	**65**: [8, 15]

Harvest windows (continued)

Instance 6, Seed 12350

1: [7, 14]	**2**: [16, 23]	**3**: [21, 28]	**4**: [23, 30]	**5**: [20, 27]
6: [17, 24]	**7**: [25, 32]	**8**: [10, 17]	**9**: [16, 23]	**10**: [21, 28]
11: [23, 30]	**12**: [22, 29]	**13**: [24, 31]	**14**: [3, 10]	**15**: [13, 20]
16: [14, 21]	**17**: [15, 22]	**18**: [3, 10]	**19**: [3, 10]	**20**: [24, 31]
21: [23, 30]	**22**: [3, 10]	**23**: [18, 25]	**24**: [3, 10]	**25**: [13, 20]
26: [23, 30]	**27**: [13, 20]	**28**: [5, 12]	**29**: [8, 15]	**30**: [21, 28]
31: [11, 18]	**32**: [15, 22]	**33**: [25, 32]	**34**: [22, 29]	**35**: [12, 19]
36: [6, 13]	**37**: [20, 27]	**38**: [16, 23]	**39**: [13, 20]	**40**: [2, 9]
41: [23, 30]	**42**: [10, 17]	**43**: [2, 9]	**44**: [24, 31]	**45**: [21, 28]
46: [11, 18]	**47**: [16, 23]	**48**: [18, 25]	**49**: [6, 13]	**50**: [24, 31]
51: [3, 10]	**52**: [19, 26]	**53**: [22, 29]	**54**: [21, 28]	**55**: [11, 18]
56: [2, 9]	**57**: [21, 28]	**58**: [22, 29]	**59**: [6, 13]	**60**: [12, 19]
61: [8, 15]	**62**: [12, 19]	**63**: [13, 20]	**64**: [9, 16]	**65**: [24, 31]

Instance 7, Seed 12351

1: [12, 19]	**2**: [22, 29]	**3**: [19, 26]	**4**: [14, 21]	**5**: [18, 25]
6: [19, 26]	**7**: [8, 15]	**8**: [6, 13]	**9**: [15, 22]	**10**: [15, 22]
11: [15, 22]	**12**: [10, 17]	**13**: [2, 9]	**14**: [16, 23]	**15**: [1, 8]
16: [8, 15]	**17**: [10, 17]	**18**: [9, 16]	**19**: [3, 10]	**20**: [7, 14]
21: [19, 26]	**22**: [25, 32]	**23**: [15, 22]	**24**: [9, 16]	**25**: [18, 25]
26: [7, 14]	**27**: [10, 17]	**28**: [24, 31]	**29**: [20, 27]	**30**: [24, 31]
31: [17, 24]	**32**: [12, 19]	**33**: [5, 12]	**34**: [23, 30]	**35**: [3, 10]
36: [12, 19]	**37**: [23, 30]	**38**: [19, 26]	**39**: [15, 22]	**40**: [17, 24]
41: [18, 25]	**42**: [14, 21]	**43**: [14, 21]	**44**: [11, 18]	**45**: [7, 14]
46: [10, 17]	**47**: [25, 32]	**48**: [10, 17]	**49**: [18, 25]	**50**: [23, 30]
51: [18, 25]	**52**: [20, 27]	**53**: [18, 25]	**54**: [15, 22]	**55**: [24, 31]

Harvest windows (continued)

56: [2, 9]	**57**: [19, 26]	**58**: [3, 10]	**59**: [21, 28]	**60**: [19, 26]
61: [20, 27]	**62**: [6, 13]	**63**: [2, 9]	**64**: [24, 31]	**65**: [4, 11]

Instance 8, Seed 12352

1: [12, 19]	**2**: [6, 13]	**3**: [4, 11]	**4**: [8, 15]	**5**: [19, 26]
6: [25, 32]	**7**: [11, 18]	**8**: [10, 17]	**9**: [16, 23]	**10**: [2, 9]
11: [3, 10]	**12**: [19, 26]	**13**: [10, 17]	**14**: [6, 13]	**15**: [25, 32]
16: [16, 23]	**17**: [4, 11]	**18**: [5, 12]	**19**: [19, 26]	**20**: [18, 25]
21: [8, 15]	**22**: [22, 29]	**23**: [7, 14]	**24**: [9, 16]	**25**: [10, 17]
26: [4, 11]	**27**: [3, 10]	**28**: [12, 19]	**29**: [3, 10]	**30**: [3, 10]
31: [18, 25]	**32**: [4, 11]	**33**: [25, 32]	**34**: [15, 22]	**35**: [20, 27]
36: [5, 12]	**37**: [7, 14]	**38**: [20, 27]	**39**: [10, 17]	**40**: [21, 28]
41: [23, 30]	**42**: [1, 8]	**43**: [14, 21]	**44**: [21, 28]	**45**: [1, 8]
46: [1, 8]	**47**: [25, 32]	**48**: [22, 29]	**49**: [21, 28]	**50**: [20, 27]
51: [15, 22]	**52**: [20, 27]	**53**: [25, 32]	**54**: [14, 21]	**55**: [2, 9]
56: [19, 26]	**57**: [7, 14]	**58**: [2, 9]	**59**: [11, 18]	**60**: [8, 15]
61: [3, 10]	**62**: [8, 15]	**63**: [17, 24]	**64**: [22, 29]	**65**: [15, 22]

Instance 9, Seed 12353

1: [12, 19]	**2**: [7, 14]	**3**: [20, 27]	**4**: [19, 26]	**5**: [22, 29]
6: [7, 14]	**7**: [17, 24]	**8**: [8, 15]	**9**: [19, 26]	**10**: [17, 24]
11: [12, 19]	**12**: [15, 22]	**13**: [5, 12]	**14**: [19, 26]	**15**: [16, 23]
16: [4, 11]	**17**: [22, 29]	**18**: [10, 17]	**19**: [23, 30]	**20**: [4, 11]
21: [5, 12]	**22**: [6, 13]	**23**: [18, 25]	**24**: [21, 28]	**25**: [7, 14]
26: [7, 14]	**27**: [20, 27]	**28**: [8, 15]	**29**: [21, 28]	**30**: [18, 25]
31: [2, 9]	**32**: [13, 20]	**33**: [23, 30]	**34**: [5, 12]	**35**: [16, 23]
36: [9, 16]	**37**: [4, 11]	**38**: [13, 20]	**39**: [5, 12]	**40**: [22, 29]

Harvest windows (continued)

41: [21, 28]	**42**: [18, 25]	**43**: [13, 20]	**44**: [19, 26]	**45**: [12, 19]
46: [8, 15]	**47**: [23, 30]	**48**: [2, 9]	**49**: [4, 11]	**50**: [2, 9]
51: [25, 32]	**52**: [11, 18]	**53**: [12, 19]	**54**: [16, 23]	**55**: [22, 29]
56: [20, 27]	**57**: [6, 13]	**58**: [19, 26]	**59**: [25, 32]	**60**: [2, 9]
61: [10, 17]	**62**: [16, 23]	**63**: [20, 27]	**64**: [17, 24]	**65**: [23, 30]

Instance 10, Seed 12354

1: [5, 12]	**2**: [9, 16]	**3**: [8, 15]	**4**: [12, 19]	**5**: [19, 26]
6: [22, 29]	**7**: [3, 10]	**8**: [21, 28]	**9**: [8, 15]	**10**: [25, 32]
11: [20, 27]	**12**: [15, 22]	**13**: [6, 13]	**14**: [2, 9]	**15**: [2, 9]
16: [9, 16]	**17**: [13, 20]	**18**: [7, 14]	**19**: [8, 15]	**20**: [11, 18]
21: [18, 25]	**22**: [19, 26]	**23**: [10, 17]	**24**: [12, 19]	**25**: [13, 20]
26: [11, 18]	**27**: [21, 28]	**28**: [3, 10]	**29**: [11, 18]	**30**: [22, 29]
31: [24, 31]	**32**: [20, 27]	**33**: [7, 14]	**34**: [6, 13]	**35**: [14, 21]
36: [8, 15]	**37**: [11, 18]	**38**: [8, 15]	**39**: [10, 17]	**40**: [7, 14]
41: [8, 15]	**42**: [12, 19]	**43**: [1, 8]	**44**: [5, 12]	**45**: [1, 8]
46: [14, 21]	**47**: [6, 13]	**48**: [1, 8]	**49**: [2, 9]	**50**: [6, 13]
51: [22, 29]	**52**: [17, 24]	**53**: [3, 10]	**54**: [14, 21]	**55**: [18, 25]
56: [13, 20]	**57**: [10, 17]	**58**: [2, 9]	**59**: [5, 12]	**60**: [9, 16]
61: [17, 24]	**62**: [10, 17]	**63**: [6, 13]	**64**: [6, 13]	**65**: [17, 24]

B: Optimal solution under max sugar content of base model

Table 35: Optimal solution under max sugar content of base model

Plot	Harvest	Mill	Process	Processed (t)	Disposed (t)
1	27	1	27	314.94	—
2	10	2	10	314.94	—
3	7	2	7	314.94	—
4	30	1	30	314.94	—
5	15	2	15	185.06	129.88 (mill 2)
6	14	2	14	314.94	—
7	14	1	14	314.94	—
8	11	1	11	314.94	—
9	30	2	30	185.06	129.88 (mill 2)
10	10	1	10	314.94	—
11	28	1	28	314.94	—
12	30	1	30	314.94	—
13	24	2	24	185.06	129.88 (mill 2)
14	9	1	9	314.94	—
15	25	1	25	317.88	—
16	20	2	20	314.94	—
17	8	1	8	314.94	—
18	7	1	7	314.94	—

Continued on next page

Table 35: Optimal solution under max sugar content of base model (continued)

Plot	Harvest	Mill	Process	Processed (t)	Disposed (t)
19	9	2	9	185.06	129.88 (mill 2)
20	13	1	13	314.94	—
21	14	1	14	314.94	—
22	23	1	23	314.94	—
23	26	2	26	314.94	—
24	7	1	7	314.94	—
25	25	1	25	314.94	—
26	13	2	13	314.94	—
27	29	2	29	314.94	—
28	27	2	27	314.94	—
29	29	1	29	314.94	—
30	24	2	24	314.94	—
31	20	1	20	314.94	—
32	14	2	14	185.06	129.88 (mill 2)
33	21	1	21	314.94	—
34	25	2	25	314.94	—
35	15	1	15	314.94	—
36	7	2	7	185.06	129.88 (mill 2)
37	31	1	31	314.94	—
38	12	1	12	314.94	—
39	29	1	29	314.94	—
40	20	1	20	314.94	—
41	17	1	17	314.94	—

Continued on next page

Table 35: Optimal solution under max sugar content of base model (continued)

Plot	Harvest	Mill	Process	Processed (t)	Disposed (t)
42	15	2	15	314.94	—
43	11	2	11	314.94	—
44	13	1	13	314.94	—
45	31	1	31	314.94	—
46	17	1	17	314.94	—
47	11	1	11	317.88	—
48	9	1	9	314.94	—
49	19	1	19	314.94	—
50	10	1	10	314.94	—
51	18	1	18	314.94	—
52	18	1	18	314.94	—
53	26	1	26	314.94	—
54	15	1	15	314.94	—
55	8	1	8	314.94	—
56	30	2	30	314.94	—
57	21	1	21	314.94	—
58	24	1	24	314.94	—
59	10	2	10	185.06	129.88 (mill 2)
60	19	1	19	314.94	—
61	9	2	9	314.94	—
62	24	1	24	314.94	—
63	16	1	16	314.94	—
64	27	1	27	314.94	—

Continued on next page

Table 35: Optimal solution under max sugar content of base model (continued)

Plot	**Harvest**	**Mill**	**Process**	**Processed (t)**	**Disposed (t)**
65	26	1	26	314.94	—

— indicates no disposal.

— indicates no disposal.

C: Capacity usage under max sugar content of base model

Table 36: Capacity utilization (%) for $\varepsilon = 2779.57$

Group A			Group B		
Period	**Mill 1 (%)**	**Mill 2 (%)**	**Period**	**Mill 1 (%)**	**Mill 2 (%)**
Harvesting Capacity Utilization					
1	0.0	0.0	2	0.0	0.0
3	0.0	0.0	4	0.0	0.0
5	0.0	0.0	6	0.0	0.0
7	74.1	74.1	8	74.1	0.0
9	74.1	74.1	10	74.1	74.1
11	74.4	37.1	12	37.1	0.0
13	74.1	37.1	14	74.1	74.1
15	74.1	74.1	16	37.1	0.0
17	74.1	0.0	18	74.1	0.0
19	74.1	0.0	20	74.1	37.1
21	74.1	0.0	22	0.0	0.0
23	37.1	0.0	24	74.1	74.1
25	74.4	37.1	26	74.1	37.1
27	74.1	37.1	28	37.1	0.0
29	74.1	37.1	30	74.1	74.1
31	74.1	0.0	32	0.0	0.0
Transport (Vehicle) Capacity Utilization					
1	0.0	0.0	2	0.0	0.0
3	0.0	0.0	4	0.0	0.0
5	0.0	0.0	6	0.0	0.0

7	52.0	52.0	8	52.0	0.0
9	52.0	52.0	10	52.0	52.0
11	52.0	26.0	12	26.0	0.0
13	52.0	26.0	14	52.0	52.0
15	52.0	52.0	16	26.0	0.0
17	52.0	0.0	18	52.0	0.0
19	52.0	0.0	20	52.0	26.0
21	52.0	0.0	22	0.0	0.0
23	26.0	0.0	24	52.0	52.0
25	52.0	26.0	26	52.0	26.0
27	52.0	26.0	28	26.0	0.0
29	52.0	26.0	30	52.0	52.0
31	52.0	0.0	32	0.0	0.0
Processing Capacity Utilization					
1	0.0	0.0	2	0.0	0.0
3	0.0	0.0	4	0.0	0.0
5	0.0	0.0	6	0.0	0.0
7	63.0	100.0*	8	63.0	0.0
9	63.0	100.0*	10	63.0	100.0*
11	63.3	63.0	12	31.5	0.0
13	63.0	63.0	14	63.0	100.0*
15	63.0	100.0*	16	31.5	0.0
17	63.0	0.0	18	63.0	0.0
19	63.0	0.0	20	63.0	63.0
21	63.0	0.0	22	0.0	0.0
23	31.5	0.0	24	63.0	100.0*
25	63.3	63.0	26	63.0	63.0
27	63.0	63.0	28	31.5	0.0
29	63.0	63.0	30	63.0	100.0*

31	63.0	0.0	32	0.0	0.0

Note: Asterisk (*) indicates the capacity constraint is binding (100% utilization).

D: Optimal Solution under max sugar of heterogeneous model

Table 37: Optimal Solution under max sugar of alternative model

Plot	Harvested period	Delivered Mill	Processed period	Processed amount(t)	Disposed amount(t)
1	27	1	27	363.50	—
2	10	2	10	200.16	97.35 (mill 2)
3	7	2	7	276.18	—
4	30	2	30	260.71	—
5	15	1	15	335.26	—
6	14	1	14	349.34	—
7	14	1	14	376.07	—
8	11	1	11	359.70	—
9	30	1	30	361.11	—
10	10	2	10	299.84	—
11	28	1	28	309.07	—
12	30	1	30	357.03	—
13	25	2	25	274.99	—
14	9	2	9	296.71	—
15	25	1	25	336.38	—
16	20	1	20	340.36	—
17	8	1	8	338.06	—
18	7	2	7	223.82	37.12 (mill 2)
19	9	1	9	331.94	—
20	13	1	13	319.24	—

Table 37 continued

Plot	Harvest	Mill	Process	Processed (t)	Disposed (t)
21	14	2	14	282.79	—
22	23	1	23	310.19	—
23	26	1	26	285.96	—
24	7	1	7	368.53	—
25	24	1	24	338.64	—
26	13	2	13	279.62	—
27	29	1	29	292.80	—
28	27	1	27	348.74	—
29	29	2	29	259.00	—
30	24	1	24	355.48	—
31	20	1	20	353.37	—
32	14	2	14	217.21	85.28 (mill 2)
33	21	1	21	260.29	—
34	25	1	25	366.99	—
35	15	1	15	323.40	—
36	7	1	7	342.39	—
37	31	1	31	278.74	—
38	12	1	12	314.84	—
39	29	1	29	363.40	—
40	20	2	20	332.94	—
41	17	1	17	269.95	—
42	15	2	15	228.79	40.75 (mill 2)
43	11	1	11	345.80	—
44	13	1	13	319.85	—

Table 37 continued

Plot	Harvest	Mill	Process	Processed (t)	Disposed (t)
45	31	1	31	346.06	—
46	17	1	17	305.92	—
47	10	1	10	325.46	—
48	9	1	9	297.55	—
49	19	1	19	377.59	—
50	11	2	11	271.89	—
51	18	1	18	314.12	—
52	18	1	18	347.16	—
53	26	1	26	360.43	—
54	15	2	15	271.21	—
55	8	1	8	272.11	—
56	30	2	30	239.29	98.39 (mill 2)
57	21	1	21	327.09	—
58	24	2	24	300.42	—
59	10	1	10	327.02	—
60	19	1	19	310.92	—
61	9	2	9	203.29	80.33 (mill 2)
62	24	2	24	199.58	122.07 (mill 2)
63	16	1	16	370.68	—
64	27	2	27	337.65	—
65	26	2	26	266.38	—

— indicates no disposal.

E: Capacity usage under max sugar content of heterogeneous model

Table 38: Capacity utilization (%) for $\varepsilon = 2807.62$

Group A			Group B		
Period	Mill 1 (%)	Mill 2 (%)	Period	Mill 1 (%)	Mill 2 (%)
Harvesting Capacity Utilization					
1	0.0	0.0	2	0.0	0.0
3	0.0	0.0	4	0.0	0.0
5	0.0	0.0	6	0.0	0.0
7	83.6	63.2	8	71.8	0.0
9	74.1	68.3	10	76.8	70.3
11	83.0	32.0	12	37.0	0.0
13	75.2	32.9	14	85.3	68.9
15	77.5	63.6	16	43.6	0.0
17	67.7	0.0	18	77.8	0.0
19	81.0	0.0	20	81.6	39.2
21	69.1	0.0	22	0.0	0.0
23	36.5	0.0	24	81.7	73.2
25	82.7	32.4	26	76.0	31.3
27	83.8	39.7	28	36.4	0.0
29	77.2	30.5	30	84.5	70.4
31	73.5	0.0	32	0.0	0.0
Transport (Vehicle) Capacity Utilization					
1	0.0	0.0	2	0.0	0.0
3	0.0	0.0	4	0.0	0.0
5	0.0	0.0	6	0.0	0.0

7	58.0	46.0	8	50.0	0.0
9	52.0	48.0	10	56.0	48.0
11	58.0	22.0	12	26.0	0.0
13	52.0	24.0	14	60.0	50.0
15	54.0	44.0	16	30.0	0.0
17	48.0	0.0	18	54.0	0.0
19	58.0	0.0	20	58.0	28.0
21	50.0	0.0	22	0.0	0.0
23	26.0	0.0	24	58.0	52.0
25	58.0	22.0	26	54.0	22.0
27	58.0	28.0	28	26.0	0.0
29	54.0	22.0	30	60.0	50.0
31	52.0	0.0	32	0.0	0.0

Processing Capacity Utilization

1	0.0	0.0	2	0.0	0.0
3	0.0	0.0	4	0.0	0.0
5	0.0	0.0	6	0.0	0.0
7	71.1	100.0*	8	61.0	0.0
9	62.9	100.0*	10	65.2	70.6
11	70.6	31.5	12	31.5	0.0
13	63.9	55.9	14	72.5	100.0*
15	65.9	0.0	16	37.1	0.0
17	57.6	0.0	18	66.1	0.0
19	68.9	0.0	20	69.4	66.6
21	58.7	0.0	22	0.0	0.0
23	31.0	0.0	24	69.4	100.0*
25	70.3	55.0	26	64.6	53.3
27	71.2	67.5	28	30.9	0.0
29	65.6	51.8	30	71.8	100.0*

31	62.5	0.0	32	0.0	0.0

Note: Asterisk (*) indicates the capacity constraint is binding (100% utilization).