Supply Chain Reallocation Problem in the Automotive Industry: A Mixed-Integer Linear Programming Approach

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Abstract

In the highly structured and cost-sensitive environment of automotive manufacturing, the efficiency of delivery scheduling plays a critical role in determining overall supply chain performance. Traditional shipment planning methods, often static and heuristic in nature, fail to exploit available flexibility in delivery windows—leading to frequent inefficiencies such as underutilized truck capacity, excessive setup frequency, and fragmented shipments. This thesis addresses these operational shortcomings through the development of a progressive suite of deterministic optimization models designed to reallocate deliveries across fixed time slots.

Three mixed integer linear programming (MILP) models are proposed, each adding successive layers of real-world complexity. The basic model introduces a time-windowed reallocation framework aimed at balancing delivery volumes and reducing setup and holding costs. The enhanced model builds upon this by incorporating truck capacity constraints and underutilization penalties to simulate more realistic logistics scenarios. Finally, the supplier-integrated model introduces supplier selection logic, binary activation decisions, and inter-supplier constraints, offering a more holistic view of cost and operational feasibility in multi-source environments.

All models are implemented using Python and the PuLP optimization library and validated using synthetic data reflective of real-world automotive delivery patterns. Results demonstrate that reallocation, even within a deterministic and disruption-free environment, can yield substantial logistics cost reductions in some cases while improving resource utilization and scheduling efficiency. The models serve not only as theoretical constructions but also as practical decision-support tools that can be embedded within existing enterprise planning systems. By systematically restructuring delivery plans before execution, this research bridges the gap between strategic supply chain theory and actionable, mid-horizon logistics planning.

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CHAPTER 1: INTRODUCTION

1.1. The History and Evolution of Supply Chain Management

Supply chain management (SCM) has evolved dramatically over the years. What once was a simple back-end function mainly handling the movement of goods has now become a key part of a company's strategy. Initially, supply chains focused on basic logistics like procurement and delivery [1]. In the early 20th century, the rise of mass production and assembly lines, especially through companies like Ford, required more structured logistics [2]. Still, concepts like inventory or transportation were treated as individual functions. It was not until the mid-20th century that supply chain thinking started to get more scientific. With the introduction of operations research, companies began using mathematical tools like linear programming and simulations to better plan their resources [3]. By the 1970s, new practices like lean manufacturing and just-in-time systems (mainly popularized in Japan) required companies to work more closely with their suppliers [4]. These developments laid the foundation for integrated supply chain management.

By the 1990s, SCM was officially recognized as a discipline, fueled by globalization, outsourcing, and the introduction of ERP systems [5]. It became clear that managing everything materials, data, and money across a network of partners was crucial. SCM turned into a multi-disciplinary field that combined logistics, IT, operations, and strategic sourcing. Today, in a technology-driven era, tools like artificial intelligence and real-time analytics have taken SCM to a new level [6]. As noted by Christopher (2016), SCM has shifted from being a separate function to becoming a core, strategic operation [7]. Chopra and Meindl (2016) emphasized how modern supply chains rely more on tech-driven collaboration and integration [8].

1.2 Overview of Supply Chain Processes

A supply chain is the full system of people, organizations, technology, activities, and resources that work together to move a product or service from the supplier to the final customer [9]. It includes everything from raw material sourcing and production to the delivery of finished goods and handling customer returns. The complexity of modern supply chains makes their coordination essential for achieving efficiency, reducing costs, and delivering customer satisfaction.

Modern supply chains are typically broken into five key functions: planning, sourcing, manufacturing, delivery, and returns [10]. These are formalized by the Supply Chain Operations Reference (SCOR) model developed by the Supply Chain Council, which provides a standard framework and performance metrics [11]. Planning is the foundation of all supply chain activity. It involves forecasting customer demand, designing the supply chain network, determining inventory levels, and allocating resources efficiently. Effective planning ensures that production meets demand without resulting in overproduction or shortages [12]. Sourcing focuses on supplier selection, procurement strategies, and managing relationships with vendors. Choosing the right supplier is not just about cost, it also involves evaluating quality, reliability, capacity, and responsiveness [13].

Manufacturing covers all the activities involved in converting raw materials into finished products. This includes production scheduling, quality control, facility management, and labor deployment [14]. Here, operational efficiency is critical, as delays or inefficiencies can quickly spoil the rest of the supply chain. Delivery and logistics are responsible for getting the product to the end user. This involves warehousing, inventory management, order processing, transportation, and distribution. Logistics also include coordinating with third-party logistics providers, optimizing shipping routes, and ensuring that deliveries are made on time and in full [15]. Returns management, often called reverse logistics, handles everything coming back from the customer, such as product returns, warranty claims, repairs, recycling, or disposal. This part of the supply chain is often overlooked but is essential for maintaining customer trust and managing environmental responsibility [16].

What makes supply chain processes particularly challenging is the need to coordinate across these areas while managing the flow of materials, information, and finances. For example, a delay in raw material delivery (sourcing) impacts production (manufacturing), which in turn affects when products can be shipped (delivery). These dependencies create a chain reaction, so decisions in one area must consider their downstream effects.

To model and manage these interdependencies, modern supply chains rely on analytics and optimization tools to manage these interdependencies. As delays in one stage affect others, companies use mathematical models like MILP to simulate and improve decisions across the entire chain [17]. This approach enables businesses to evaluate trade-offs, consider constraints, and find the most cost-effective and feasible solutions. The SCOR model, developed by the supply chain council, provides a useful framework to understand and structure these processes. It defines standardized components and performance metrics, which help businesses benchmark and continuously improve their supply chain operations.

1.3 Supply Chain Management in the Automotive Industry

SCM in the automotive industry is highly complex due to the large volume of parts and global sourcing practices [18]. A single car can include over 30,000 individual parts, sourced from suppliers all over the world. These parts are delivered through a tiered supplier system. Tier 1 suppliers work directly with manufacturers, while Tier 2 and Tier 3 supply the upstream suppliers. To manage this massive web of suppliers, car manufacturers rely heavily on systems like Just-In-Time (JIT) and Just-In-Sequence (JIS) delivery [19]. JIT ensures parts arrive exactly when needed, which minimizes inventory costs. JIS takes this further by ensuring that parts show up not just on time, but in the precise order they'll be used during assembly. While this increases efficiency, it also makes the system more fragile, any small delay can cause a chain reaction.

Customization adds another layer of complexity. With customers expecting personalized vehicle features, manufacturers must handle low-volume, high-mix components alongside standard ones. This requires precise scheduling, tight delivery windows, and constant coordination with suppliers. Even slight inefficiencies, like sending half-empty trucks or poor delivery timing, can drive up logistics costs significantly. The optimization models in this thesis aim to tackle those issues by rethinking delivery schedules rather than reacting to problems after they happen [20].

1.4 The Concept of Supply Chain Reallocation

Supply chain reallocation is about making the most of existing delivery plans by shifting shipments across different time windows or delivery slots in a planned, strategic way. Unlike disruption management, which reacts to unexpected issues, reallocation works with a known set of inputs such as costs, demands, and capacities and looks for ways to improve efficiency proactively [21]. For example, a delivery originally scheduled for 7 PM could be rescheduled to an earlier slot, such as 11 AM the same day, if truck capacity and operational constraints allow. This type of proactive rescheduling may help reduce inventory holding costs or improve truck utilization by consolidating loads. We could also combine multiple small deliveries into a single full truckload, cutting transportation costs. Or we might even decide to place an order from a different supplier if it is cheaper.

This introduces a significant operational challenge. We must balance many different cost factors like unit cost, holding fees, setup charges, and penalties for unused truck space. On top of that, we need to work within limits like truck capacity, time windows, and which suppliers are available. Hence the reason why in this study we use MILP models to approach the problem [22]. These tools are well-suited for handling complex decisions within strict constraints.

1.5 Background and Problem Statement

In traditional supply chain operations, shipment schedules are usually set in advance and followed with little to no change unless a disruption occurs. These plans are often developed based on estimated demand and fixed time slots and are designed more for stability than optimization. While this static approach may work under predictable conditions, it can lead to various inefficiencies that increase overall logistics costs [23]. This is especially true in complex industries like automotive manufacturing, where frequent deliveries, tight deadlines, and thousands of moving parts create a highly dynamic environment.

One major issue with fixed scheduling is the underutilization of transportation resources. For example, companies may dispatch trucks that are only partially loaded simply to meet a planned delivery slot. Each of these trips incurs a setup or usage cost regardless of whether the truck is fully loaded. In environments where multiple deliveries occur daily such as a supplier making five separate trips to a manufacturing plant, this can result in high logistics expenses due to frequent setups, fragmented shipments, and underused truck capacity.

Another issue arises from uneven shipment distribution throughout the planning horizon. If deliveries are unevenly spread. say, heavier loads in the morning and lighter ones in the evening, this imbalance may lead to bottlenecks, increased inventory holding costs, and poor utilization of time-sensitive resources. Additionally, when multiple product types are involved, there may be missed opportunities to consolidate shipments or reassign items to more efficient time windows, which could reduce overall costs significantly [24].

What makes this problem more challenging is the presence of multiple real-world constraints that must be respected. Deliveries can only be reallocated within a defined time window (referred to as the pull-ahead limit), and truck capacities cannot be exceeded. Each delivery also triggers a setup cost, whether it is necessary or not. Furthermore, when more than one supplier is involved, additional factors such as supplier-specific costs, delivery availability, and operational limitations further complicate decision-making.

In the absence of a structured optimization approach, most logistics planners rely on heuristics or experience-based rules to adjust delivery plans, often leading to sub-optimal results. While these manual adjustments may address immediate needs, they do not guarantee cost-effective outcomes across the entire supply chain.

This thesis addresses this gap by developing a series of optimization models designed to intelligently reallocate shipment plans within a feasible planning horizon. The models aim to minimize total logistics costs including unit cost, setup cost, holding cost, trucking cost, and penalties for underutilized truck space while satisfying all relevant operational constraints [25]. These models are built using MILP, which is well-suited for representing discrete decisions (such as whether a truck is used or not) and continuous flows (such as quantities delivered).

The models are implemented in Python and tested with synthetic data that mimics conditions in automotive logistics. Through a progression of models starting with a basic MILP framework and moving toward a supplier-integrated, multi-item environment this study demonstrates how mathematical optimization can lead to smarter, more cost-efficient planning in complex supply chain networks.

1.6 Research Objectives

This research is focused on building mathematical models that help improve delivery plans across a supply chain by reallocating shipments to lower total logistics costs. The models do this while respecting real-world constraints like truck capacity, delivery windows, and supplier activity. The specific goals are:

- Build a basic MILP model for a simple supply chain with a single item and supplier, optimizing unit, setup, and holding costs.

- Expand the model to handle multiple items and include truck constraints for a more realistic logistics scenario.
- Add supplier-related decisions into the model to handle inter-supplier reallocations and unused truck penalties.
- Implement all three models in Python and test them using synthetic data.
- Compare the performance of each model in terms of cost, scalability, and delivery efficiency.

1.7 Research Questions

The study is guided by these research questions:

- How can shipment reallocation be modeled to reduce logistics costs without missing delivery targets?
- What is the impact of including truck usage and setup costs in reallocation planning?
- How does factoring in supplier selection influence total cost and efficiency?
- Can these models handle large-scale, complex logistics scenarios?
- Can the models help logistics managers make better delivery planning decisions in automotive supply chains?

1.8 Significance of the Study

With increasing market pressures and global competition, organizations are expected to do more with less deliveries faster, more reliably, and at a lower cost. Traditional planning methods, which often lack optimization and flexibility, are no longer sufficient. This is where the research becomes especially relevant.

Most existing research has concentrated on handling uncertainty and risk, whereas this study explores how to improve efficiency even when all variables are known in advance. The introduction of a progressive modeling approach starting from a basic model and evolving into an enhanced and then supplier-integrated model presents a novel methodology that is both scalable and adaptable. The use of MILP is particularly noteworthy, by developing models that reflect real-world operational constraints like time windows, truck capacity limits, and supplier activation costs, this research bridges the gap between theoretical modeling and practical implementation

[27]. These models are not just academic exercises but are designed to serve as decision support tools that logistics planners and supply chain managers can adopt and apply in real industrial settings.

On a practical level, the findings offer valuable insights for supply chain professionals looking to optimize logistics operations without needing major infrastructure investments or complex IT overhauls. The models help identify how minor adjustments such as reallocating shipments or better utilizing truck capacity can lead to substantial cost savings. This is especially beneficial for companies operating in tightly scheduled, cost-intensive supply chains like those in automotive, electronics, or fast-moving consumer goods.

Moreover, the modular design of the models makes them flexible and extendable. Depending on the company's size and complexity, the models can be scaled up or down. For smaller businesses, the basic MILP model offers a simplified optimization path. For larger enterprises dealing with multiple suppliers and thousands of SKUs, the supplier-integrated model provides a comprehensive solution.

In essence, this research empowers supply chain professionals with data-driven tools to make smarter, more informed decisions. It promotes the idea that significant improvements in efficiency and cost-effectiveness can be achieved not through drastic change, but through smarter planning based on mathematical models. This makes the study highly relevant for organizations aiming to remain competitive in today's fast-paced and cost-conscious markets.

CHAPTER 2: LITERATURE REVIEW

2.1 Automotive Supply Chain Structure and Reallocation Needs

The automotive supply chain is a multi-tiered, synchronized system structured around JIT and JIS principles, which require parts to be delivered precisely and in sequence [28]. Modern vehicle manufacturing is driven by just-in-time (JIT) and just-in-sequence (JIS) philosophies, where components must arrive at the assembly line not only on time but in the precise order of assembly. Unlike traditional inventory based industries, the automotive supply chain is designed to operate with minimal stock buffers, which elevates the importance of accurate, slot-based delivery planning. A typical car comprises between 15,000 and 25,000 individual components, sourced globally from Tier 1, Tier 2, and Tier 3 suppliers [29]. These suppliers operate under tightly negotiated contracts, delivering goods to OEM plants across defined delivery windows often in multi-slot daily time frames.

In this context, delivery planning is not merely about assigning quantities to a calendar date, but about sequencing shipments into defined time slots, optimizing transport assets like trucks, and avoiding the costly overhead of underutilized vehicles or unplanned supplier setups. The frequency of deliveries, especially for high-demand parts such as seats, dashboards, or electronics, results in multiple shipments per day. This exposes Inefficiencies arise from partial truck loads and frequent supplier setups, which increases logistics cost [30]. Reallocation of shipments across known slots, rather than responding to disruptions, provides deterministic cost optimization opportunities [31]. Importantly, unlike disruption-oriented supply chain models that rely on stochastic programming, the need here is for deterministic optimization: reallocating known quantities within fixed delivery frameworks to reduce cost while maintaining service level adherence.

From an operational standpoint, current enterprise resource planning (ERP) systems often generate static shipment schedules based on demand forecasts and lead times. These plans lack the flexibility to dynamically reshuffle or pull deliveries ahead into earlier windows to exploit opportunities for truck consolidation or setup reduction [32]. Reallocation, therefore, becomes a mid-term planning decision that can be mathematically optimized, especially in a deterministic environment where all variables -demand, capacity, costs are known at planning time. This thesis directly addresses this context by proposing MILP models that reallocate delivery quantities across slots within strict operational boundaries, aiming to reduce unit, setup, and transportation costs without altering the total demand or introducing uncertainty [33].

2.2 Operational Challenges in Slot-Based Automotive Delivery Planning

In high-frequency automotive supply chains, the challenge is not only about fulfilling orders on time but doing so with optimal use of resources such as trucks, supplier setups, and storage space. Most suppliers face daily or sub-daily shipment schedules, often delivering to multiple OEMs and plants. Each delivery may incur fixed setup costs such as production line activation, order processing, or paperwork irrespective of the quantity shipped. When deliveries are fragmented across many time slots, these setup costs can escalate rapidly. Similarly, trucks dispatched at low-capacity utilization incur transportation inefficiencies, increasing per-unit cost due to wasted volume [34]. However, existing shipment schedules generated by basic planning tools often fail to address these inefficiencies holistically.

One of the core operational pain points in delivery planning is lack of reallocation flexibility. While ERP systems assign quantities to time slots based on earliest requirement dates, they do not assess the impact of moving deliveries slightly forward (within a pull-ahead limit) to fill trucks more efficiently or reduce redundant setups. The reallocation problem, therefore, is about restructuring shipment volumes within the same total horizon, ensuring that no future demand is lost, while reducing the cost of logistics execution [35]. This is a deterministic optimization problem by nature, with clear and fixed inputs: delivery dates, item quantities, supplier capacities, truck dimensions, and cost coefficients.

Reallocation also becomes a multi-dimensional problem when multiple items are involved. A supplier may send several SKUs per shipment, each with distinct volumetric profiles, costs, and delivery urgencies. Consolidating such deliveries requires careful capacity balancing, where pulling ahead one item may crowd out others. Furthermore, suppliers often operate under strict capacity constraints both in production and logistics and cannot absorb arbitrary reallocations without consequences [36]. To optimize such a system, one needs a model that simultaneously respects the binary nature of setup decisions, capacity constraints of trucks, time-slot constraints of delivery windows, and volumetric penalties for underutilization. Such a problem fits squarely within the domain of MILP modeling, where continuous (quantity) and binary (activation) variables are combined in a cost-minimizing objective function.

The literature reveals a lack of integrated models that deal with these practical realities of automotive logistics. While vehicle routing problems (VRPs) and inventory-location models have been widely studied, few deterministic formulations exist that specifically target delivery reallocation across fixed time slots, with simultaneous modeling of setup, unit, and transport costs. This gap motivates the need for advanced MILP formulations, like those proposed in this thesis, which begin with a basic reallocation logic and progressively incorporate real-world constraints such as multi-item planning and supplier integration [37].

2.3 Deterministic MILP Models for Slot-Based Delivery Optimization

MILP has long been established as a mathematical framework for handling constrained optimization problems in supply chains. For deterministic environments where all input parameters such as demand, capacity, costs, and delivery time windows are known MILP enables highly granular modeling of logistics processes [38]. Unlike stochastic or heuristic approaches that account for uncertainty or randomness, deterministic MILP models are ideal for structured mid-term planning, such as reallocation of deliveries across known future time slots. This makes them especially suitable for automotive industry scenarios where shipment volumes, supplier capacities, and time-window structures are defined upfront.

Several studies have explored deterministic MILP for delivery and vehicle planning. For instance, Guerrero et al. developed a deterministic inventory-location-routing MILP model that incorporates vehicle fixed costs and delivery scheduling within a known planning horizon. Their model explicitly addresses vehicle usage patterns and penalizes underutilization [39]. Similarly, Díaz-Madroñero et al. proposed a deterministic MILP model that integrates production and procurement transport decisions, emphasizing delivery synchronization and cost balancing—a vital consideration in the model where multi-slot delivery windows require coordination of suppliers and transport assets [40].

More recently, Fontaine et al. introduced a MILP model specifically for automotive inbound logistics. Their formulation considers truck utilization, fixed transport costs, and supplier delivery patterns across a deterministic time horizon. They highlight how truck underutilization can be penalized via cost terms, using linear penalties. The study validates the importance of modeling truck cost as a function of volume occupied, not just binary usage [41].

Another closely aligned study is by Borumand & Nookabadi, who formulated a deterministic MILP for integrated fleet sizing and routing with simultaneous delivery and pickup. While their focus is a closed-loop supply chain, the model structure incorporates fixed vehicle usage costs and load balancing over time windows, offering methodological blueprint for reallocation scenarios [42].

What unites these works is the shared objective of optimizing shipment allocations, vehicle loading, and setup costs within known operational boundaries. These models emphasize binary variables for truck usage and supplier activation, linear variables for quantity flows, and constraints for volume, demand satisfaction, and capacity [43].

2.4 Delivery Reallocation Logic in Slot-Based Supply Chains

The core motivation behind the basic Model of this thesis is the realization that static shipment schedules those pre-assigned by traditional ERP and planning systems often do not reflect cost-efficient delivery patterns. In real-world automotive logistics, deliveries are organized into predefined time slots, often segmented into multiple delivery windows per day over a fixed planning horizon (typically weekly or bi-weekly) [44]. Once the shipment schedule is generated, these assignments are rarely revisited or optimized further. However, the shipment landscape is inherently dynamic in terms of capacity utilization, supplier readiness, and delivery urgency. Yet, the actual data used in planning quantities, due dates, and available delivery slots are typically deterministic and known in advance, making the case for optimizing the use of these resources before execution begins.

The concept of delivery reallocation, as introduced in this thesis, specifically targets this underexplored but operationally critical phase. It refers to the process of shifting planned quantities from their original assigned slots into earlier available slots within a permissible time window (e.g., a 72-hour pull-ahead limit) to consolidate deliveries, reduce fixed costs, and optimize logistics usage. Importantly, the model does not alter total delivery volumes or introduce new slots. Rather, it redistributes existing demand across time to improve cost efficiency [45]. This is particularly relevant in deterministic settings, where future demand and operational boundaries are known and reliable. The model assumes no stochastic behavior such as demand fluctuation, lead time uncertainty, or unplanned disruption allowing the optimization process to focus solely on cost structure improvements through smart allocation.

Existing literature has rarely addressed this specific problem formulation in depth. Guerrero et al. proposed an inventory-location-routing model that integrates delivery scheduling, but it lacks intra-horizon reallocation logic; the focus is on determining routes rather than improving shipment density through timing. Fahmy et al. introduced delivery volume consolidation over defined slots, allowing for early delivery (pull-ahead) strategies [46], which is conceptually aligned with our thesis. However, their model is focused on hub design and did not isolate the value of reallocation logic on its own. In contrast, our model isolates reallocation as a standalone strategic decision and measures its impact in terms of reduced unit cost and minimized fragmentation without involving supplier or trucking constraints.

A key insight from the reallocation model is the trade-off between shipment smoothing and cost minimization. While moving quantities forward can lead to cost savings (e.g., reducing fixed setup cost per slot), it also risks overloading earlier slots or creating inefficient space utilization if truck constraints are not considered. Therefore, in the model, we introduce constraints that allow shifting only within defined bounds (e.g., within 72 hours), ensuring that real-world operational feasibility is preserved. The objective function in this context is relatively simple but practical minimize the sum of delivery costs across slots while preserving demand fulfillment per item and per day. This sets the foundation for more complex models in subsequent sections, where truck and supplier constraints are layered in.

Recent papers have also acknowledged the importance of slot-based delivery logic. Zhang et al. worked on time-windowed delivery consolidation for JIT systems and highlighted how deterministic planning can lead to cost-effective improvements without disrupting downstream operations [47]. Their work confirms that even in stable environments, cost savings of 10–20% are possible through intra-week delivery reallocation. However, their model did not consider multi-slot intra-day reallocation or fine-grained pull-ahead rules, both of which are critical in the automotive context where multiple deliveries occur per day and components must meet plant-level just-in-sequence requirements.

In essence, the basic model proposed in this thesis serves as a minimal but powerful extension to standard delivery planning logic. It introduces a mathematical reallocation layer that allows logistics planners to reshuffle shipment quantities across allowable slots, with no need to change suppliers, vehicle types, or scheduling policies. It is this foundational logic reallocation under deterministic conditions that sets the stage for more integrated models that include truck utilization, multi-item bundling, and supplier activation, all of which are explored in subsequent chapters [48].

2.5 Truck Volume Utilization & Cost Optimization in Reallocation Planning

As delivery frequencies increase and shipment windows narrow in modern automotive logistics, the inefficiency of underutilized transport assets becomes a key cost driver. While traditional delivery planning systems ensure that material reaches assembly lines on time, they often ignore the economic implications of sending trucks partially full [49]. This oversight results in significant transportation waste, especially when suppliers ship small loads across multiple time slots rather than consolidating deliveries. The enhanced model in this thesis responds directly to this operational inefficiency by integrating truck volume utilization and cost minimization into the reallocation decision process [50]. The focus shifts from merely assigning quantities to slots (as in the basic model) to strategically selecting delivery configurations that optimize space usage, minimize setup frequency, and reduce costs per unit delivered.

Truck utilization optimization in this context involves a combination of binary and continuous decisions. Binary variables capture whether a truck is used in a particular slot (which triggers a fixed cost), while continuous variables represent the volume or quantity loaded. Rather than maximizing utilization, the enhanced Model minimizes cost due to underutilization more realistically with how logistics budgets are structured in actual automotive plants. Fontaine et al. developed a delivery optimization model for automotive inbound logistics that explicitly penalized underused truck volume using linear cost terms. Their results demonstrated that small shifts in delivery timing could produce 12–18% reductions in transport cost, purely through better truck fill rates [41]. Similarly, Baykasoğlu et al. reviewed deterministic fleet sizing models and highlighted that fixed truck activation costs, when not combined with volume constraints, lead to fragmented and cost-inefficient delivery networks [51].

The enhanced model improves upon the basic model by introducing volumetric constraints, ensuring that any reallocated quantity must not only satisfy delivery requirements but also fit within the truck's physical space. This is essential for automotive parts, where delivery batches may include items with different dimensional profiles, some bulky but light, others compact but dense. The model can be extended to include SKU-specific volumetric conversion factors, enabling even more realistic packing simulations. However, even in its simplest form (aggregate volume constraints per slot), the enhanced model allows planners to identify "thin deliveries" that could be reallocated forward and packed alongside other shipments to achieve cost-effective consolidation.

An equally important component of the enhanced model is the trade-off between setup frequency and delivery volume per slot. Frequent deliveries increase setup costs and resource consumption at both ends (supplier and receiver). Reducing delivery frequency through volume bundling helps reduce these fixed costs. This mirrors the logic presented in Ghiani et al. who noted that reducing the number of activated deliveries per planning period could lower operational costs by up to 20% in high-frequency systems [52]. However, they did not apply this insight to reallocation logic.

From a methodological perspective, integrating truck usage logic into reallocation planning ensures that delivery plans not only fulfill operational requirements but also satisfy economic constraints. The enhanced model strikes a balance between flexibility and realism. It retains the deterministic foundation of the basic model but layers on a realistic representation of how underused transport assets drive up total cost. In doing so, it bridges the gap between planning (which ERP systems handle) and execution (where costs are incurred), allowing logistics decision-makers to simulate and select delivery patterns that optimize transport efficiency without requiring systemic changes to suppliers or routing plans.

In summary, the enhanced model provides a practical middle layer between idealized planning and complex real-world logistics. It builds upon reallocation logic and grounds it in economically sound delivery cost modeling, specifically focusing on the real financial waste of underutilized trucks [53]. By doing so, it sets the stage for the supplier integrated model, where truck logic must interact with supplier-specific constraints raising the complexity but also the fidelity of the optimization framework.

2.6 Supplier Activation, Setup Costs, and Multi-Supplier Coordination

One of the defining complexities in modern automotive logistics is the need to coordinate deliveries from multiple suppliers, each with their own production constraints, setup requirements, and cost structures. While many traditional delivery optimization models assume a uniform supplier source or treat all suppliers as interchangeable nodes, this assumption fails to reflect the operational realities in multi-tier automotive networks. The supplier integrated model in this thesis is built precisely to capture this inter-supplier diversity by introducing setup costs and binary activation logic, allowing the delivery plan to selectively engage suppliers only when beneficial [54]. This ensures that the delivery network is not only cost-efficient from a transportation perspective but also operationally lean in terms of supplier effort and capacity use.

The inclusion of setup costs in supplier activation logic is more than just a modeling feature, it reflects real costs incurred in practice. These may include line setup time, administrative work, overtime premiums, packaging processes, or staff assignment for each delivery slot. Even if the quantity shipped is small, the moment a supplier must initiate a shipment, these costs are incurred. Traditional models that ignore this fixed setup cost component can mistakenly spread delivery quantities across multiple suppliers and slots, creating a fragmented, high-cost logistics plan. The Supplier integrated model mitigates this risk by using binary decision variables for supplier activation per slot. This enables the model to enforce realistic cost penalties for unnecessary delivery fragmentation while optimizing multiple supplier and truck options.

This approach is well-supported by recent literature. Fahmy et al. developed a deterministic planning model for supplier aggregation hubs, incorporating setup penalties for each supplier-truck combination. Their study showed that delivery costs could be reduced by over 15% simply by limiting the number of active suppliers per day and reallocating delivery volumes across fewer, better utilized shipments [46]. Similarly, Goel and Gruen emphasized that supplier-related overheads are often underrepresented in MILP models, and that including setup costs can improve the feasibility and profitability of tactical delivery plans [55].

A reallocation model that shifts volume forward must verify whether the intended supplier can support the consolidated delivery without breaching daily or slot-based capacity constraints. Furthermore, the model supports selective supplier engagement, allowing planners to route delivery volumes to the most cost-effective supplier at any given time. This resembles a multi-source allocation problem, where the system can choose not only how much to deliver and when, but also who should fulfill the order. However, unlike classic supplier selection models which optimize over periods or products, this model works at a higher resolution per slot, per item, incorporating setup costs and truck utilization simultaneously. The result is a much more operationally relevant model that reflects real-world constraints and allows for intelligent trade-offs between supplier engagement, shipment consolidation, and transportation cost.

Recent advancements in integrated delivery planning echo the need for such models. In their study on supplier-capacitated delivery planning, Yan and Tang incorporated binary activation and supplier constraints in a deterministic framework, showing how delivery fragmentation can be reduced with coordinated supplier planning [56]. Their work, although not specific to the automotive industry, supports the notion that granular supplier modeling enhances plan robustness and cost efficiency.

What distinguishes this supplier integrated model from prior literature is its simultaneous integration of three critical layers:

- Delivery reallocation across fixed slots,
- Truck volume utilization and cost penalties,
- Supplier activation and capacity limits.

While many studies address these components in isolation, this model fuses them into a cohesive deterministic planning framework that can be solved using MILP [57]. It offers a structured way for logistics managers to simulate and compare delivery configurations, reducing not only transport waste but also supplier workload and delivery overheads. As a result, it bridges the gap between long-term strategic supplier selection models and short-term execution-based shipment planning tools.

2.7 Case Studies Supporting Delivery Reallocation and Coordination in Automotive Logistics

While many supply chain models are conceptual or simulation-based, a growing body of case studies demonstrates the practical value of deterministic planning, especially in high-volume, time-sensitive industries like automotive. These studies validate the premise of this thesis: that fixed, mid-horizon reallocation of delivery volumes combined with truck and supplier constraints can lead to measurable cost savings and operational gains.

One of the most notable studies comes from Carvalho, Naghshineh, and Govindan, who investigated a Tier-1 automotive supplier's upstream network to analyze how inventory and delivery decisions impact just-in-time performance. They applied a deterministic framework to evaluate delivery delays, capacity imbalances, and supplier activation frequency [58]. Their findings confirmed that capacity-aware, deterministic reallocation could mitigate delays without increasing inventory holding costs, directly supporting the logic of this thesis's basic and enhanced models.

Another foundational example is Holweg and Pil, who conducted a longitudinal case study across three automotive manufacturers. They analyzed delivery structuring under different organizational and planning models. Their work demonstrated that deterministic decision-making includes fixed time slots and supplier coordination offers better control over cost, especially in complex multi-tier networks [59].

A third contribution comes from Pan and Nagi, who presented a deterministic planning algorithm for synchronizing production and vehicle loading in agile automotive manufacturing. Their study showed that slot-based coordination with truck constraints (fixed cost per vehicle, minimum fill rate) can reduce overall transport costs by 14–21%, compared to static ERP-generated plans. This aligns closely with enhanced model for underutilized trucks [60].

From a supplier coordination perspective, Ghasemi et al. developed a decentralized supply chain model for the British automotive sector that incorporated deterministic planning of delivery schedules and supplier activation [61]. Their framework handled multi-supplier decision-making with fixed setup costs just as in supplier integrated model and used real case data to demonstrate that supplier rationalization combined with reallocation reduced costs by 18%.

Bagul and Mukherjee investigated centralized vs. decentralized coordination in a multi-tier automotive supply chain in India [62]. Their model integrated deterministic lead times, truck constraints, and slot-based delivery decisions. Their empirical case highlighted the benefits of unified planning systems over fragmented supplier-led decisions and provided evidence for integrating truck utilization and supplier activation cost logic into central models.

These case studies collectively support the structural logic of this thesis:

- Reallocation within a deterministic horizon leads to better consolidation and reduced shipment cost.
- Truck usage penalties (fixed cost or volume inefficiency) create real incentives for re-optimization.
- Supplier activation and slot-based constraints must be respected to build practically feasible delivery schedules.

Yet, despite this alignment, no single case integrates all three components delivery slot shifting, volumetric truck modeling, and supplier activation into a unified deterministic MILP framework.

2.8 Research Gaps and Thesis Motivation

The preceding literature review illustrates significant progress in delivery optimization and supplier coordination across automotive supply chains. Numerous studies have employed deterministic models to improve planning performance, reduce transportation waste, and manage supplier engagement. However, this thesis identifies a critical methodological and practical gap that remains largely unaddressed: the absence of an integrated reallocation framework that combines slot-based delivery planning, truck utilization, and supplier activation, within a purely deterministic and executable planning window.

Firstly, while many models address delivery scheduling or truck routing, few explore delivery reallocation across fixed slots within a defined mid-term horizon, the cornerstone of this research. Most ERP systems generate shipment schedules based on earliest requirement dates, without revisiting those decisions unless there are disruptions. Yet, in a deterministic context where demand, volume, capacity, and truck dimensions are known mid-horizon reallocation presents a high impact opportunity for cost optimization. Existing works such as Zhang et al. or Fontaine et al. acknowledge this but treat it either implicitly or as a secondary effect of routing or hub design [41][47].

Secondly, truck utilization is often considered only at the macro level (fleet sizing or total load planning), not in the slot-specific volumetric framework proposed in the enhanced model. The review shows that while truck capacity constraints are common, few deterministic planning models penalize partial loads in fixed slots, especially in conjunction with reallocation decisions.

While supplier selection models incorporate setup costs at a strategic level, operational reallocation models rarely simulate binary supplier activation decisions at the slot level. This thesis addresses that omission by modeling supplier availability, slot-based engagement, and maximum delivery capacities per slot, allowing for a realistic and cost-driven selection of which supplier should be active, when, and for which items.

Most importantly, no existing study or model fully integrates all three dimensions reallocation logic, truck volume penalties, and supplier setup constraints into a unified deterministic MILP framework as proposed here. This is the primary contribution of the thesis: to present and compare three models (basic, enhanced, and supplier integrated), each building upon the last to more closely mirror the complexities of real-world automotive logistics without relying on stochastic parameters or simulation assumptions.

Furthermore, most case studies do not provide modular model comparisons. This thesis offers a rare, structured progression, showing how each model layer reallocation, truck efficiency, supplier constraints add explanatory and cost-saving power. The design allows practitioners to selectively implement models depending on the level of operational control and data availability, making the research both theoretically sound and practically relevant.

2.9 Using MILP and Python-Based Implementation in Model Development

A central methodological foundation of this thesis lies in the use of MILP to formulate and solve the delivery reallocation problem in a deterministic automotive logistics context. MILP is a mathematical optimization framework capable of handling both continuous variables (e.g., delivery volumes, truck capacity usage) and discrete or binary variables (e.g., supplier activation, setup status). Its deterministic nature makes it ideal for structured mid-term planning problems where all parameters such as demand, slot availability, truck capacity, and supplier constraints are known and stable [38]. This precisely mirrors the scope of this study, which explicitly excludes stochastic elements such as demand variability or disruption modeling.

MILP has been widely adopted in academic and industrial literature for its flexibility and accuracy in modeling real-world logistics systems. Studies such as Fontaine et al. and Guerrero et al. demonstrate how MILP enables granular modeling of delivery patterns, fixed cost penalties, and truck loading decisions under deterministic assumptions [41][39]. These models have achieved significant reductions in cost and setup frequency by optimizing delivery assignments across available time slots. Furthermore, Ghiani et al. showed that MILP based slot scheduling can improve truck fill rates and reduce unnecessary supplier dispatches [52]. These works validate MILP as a sound theoretical and practical basis for deterministic logistics planning, particularly in environments where high-frequency deliveries and supplier coordination are required.

In the context of this thesis, MILP serves as the backbone for all three proposed models:

- The basic model leverages time-indexed continuous variables and constraints to reallocate delivery volumes within a pull-ahead window, minimizing overall delivery cost.
- The enhanced model introduces binary truck usage variables, allowing the MILP formulation to capture volume-related cost inefficiencies and fixed transport charges.
- The supplier integrated model expands further with binary supplier activation variables, supplier-specific setup costs, and capacity constraints an area where MILP’s hybrid variable structure is particularly effective.

Equally important is the computational implementation of these MILP models. This thesis employs the PuLP library in Python, an open-source modeling tool that allows for seamless construction and solving of linear and integer programming problems. PuLP serves as an interface to MILP solvers like CBC (default), CPLEX, or Gurobi. Its choice is justified for several reasons:

- Transparency and Accessibility: Python is widely used in academic and professional environments, and PuLP offers a readable, adaptable codebase that aligns with reproducibility goals.

- Integration with Data Pipelines: Python integrates easily with Excel, CSV, and databases, making it ideal for future extensions of the models to real industry datasets.

- Solver Flexibility: PuLP is solver-agnostic, meaning it can be connected to high-performance solvers like Gurobi or CPLEX when computational scalability is required.

- Validation in Literature: Recent studies such as Borumand & Nookabadi and Fahmy et al. have used Python-based MILP modeling environments to simulate complex supply chain problems, validating both its practicality and accuracy for deterministic multi-constraint planning scenarios.

The use of PuLP and Python also facilitate structured experimentation with model variations and instance scaling. This is essential for this thesis, where each model (basic, enhanced, and supplier integrated) needed to be compared across multiple delivery scenarios, including single-item, multi-item, and multi-supplier test cases.

System Configuration for Model Execution:

The models were executed on a personal computer with the following specifications:

- Processor: Intel® Core™ i7-12700H CPU @ 2.30GHz

- RAM: 16 GB DDR4

- Operating System: Windows 11 Pro (64-bit)

- Solver: CBC (Coin-or branch and cut) default PuLP solver

For larger datasets or industrial applications, more advanced solvers (e.g., Gurobi or CPLEX) and higher-performance hardware may be recommended.

CHAPTER 3: MODELS AND METHODOLOGY

3.1 Introduction

This chapter presents the basic, enhanced and supplier integrated (MILP) models that are created to address the reallocation of the supply chain by optimizing the logistics costs within the constraints of operations. Its major constraints costs related to setting up processes as well as serving demand in the best possible way with available resources. It presents a framework for solving such intricacies of supply chain optimization through the implementation of this model using a python environment. The model's outcome is discussed to demonstrate the strengths and weaknesses of the model and pave the way for further improvements.

3.2 Basic Model

This basic MILP model is the starting point for developing a solution for the supply chain reallocation problem. It also employs the techniques of linear optimization to cut expenses that would be incurred in satisfying the needs of the logistics system. This is especially the case bearing in mind that all the components of the model are concentrated in relation to the objective function, decision variables, and constraints. The problem focuses on optimizing the supply chain system for a single supplier delivering a single item type to a manufacturing plant over a predefined planning horizon. The objective is to develop a reallocation plan that minimizes total costs while ensuring all demand is met.

We assume that a single supplier delivers a single item type to a manufacturing plant. The planning horizon consists of 5 to 35 discrete time periods (it is assumed that there are 5 time slots per day over a 7-day period). An initial shipment plan is created to meet the plant's demand, specifying the quantity of items to be shipped in each period. The shipment plan can be adjusted by reallocating items to earlier time periods within a predefined pull-ahead period (e.g., 72 hours). The following assumptions are considered for developing this basic model

- Multiple delivery schedules are available per day.
- Delivery schedules specify the time the truck departs from the supplier to the plant.
- Each day has the same number of time frames during the planning period.

- Shipment quantities can be reallocated to earlier time frames within a predefined period, referred to as the "pull-ahead period." For example, if we fix the pull-ahead period in hours (e.g., 6 hours). Items scheduled for a 7 PM time slot on day 4 can be reallocated to the 1 PM time slot on day 4, but not earlier than that.

- Reallocate demand to the time slot with zero delivery plan

Table 3.1 Reallocation Example (6-hour Pull-ahead period)

	11:00 AM	1:00 PM	3:00 PM	5:00 PM	7:00 PM
Day 1	100	0	50	200	100
Day 2	100	0	200	200	50
Day 3	50	50	150	50	0
Day 4	0	0	0	100	100

As observed in **Table 3.1** certain time slots (e.g., 1:00 PM on Days 1 and 2) have no scheduled shipments, while others (such as 5:00 PM on Day 1) show significant volume. This uneven distribution presents potential opportunities for shipment reallocation.

3.2.1 MILP formulation

Optimization models typically include the following elements: Objective function, decision variables and constraints**.** The proposed problem considers only one type of item being delivered. Truck-related constraints, such as space utilization or trucking costs, are not considered. There is no cost associated with reallocating items to earlier time periods. Penalties for empty space or trucking costs are excluded. The goal is to minimize the total operational cost, which can be expressed as the sum of unit, setup, and holding costs.

For the decision variables let us consider,

$x_{ij} \geq 0$: Quantity moved from period i to period j, where $i \geq j$. It is a positive integer variable.

$y_i \in \{0,1\}$: Binary variable indicating if a setup occurs in period i.

The main objective function in this model will mainly focus on minimizing the basic costs incurred, mainly the unit cost, setup cost and the holding costs.

Minimize Total Cost (Z) = Unit Cost + Setup Cost + Holding Cost

Unit Costs: unit costs are calculated based on the units moved from period j to period i, multiplied by the unit cost per unit for the destination period i. so, we generalize the equation

$$\text{Unit Cost } = \sum_{i=1}^{n}\sum_{j=1}^{i} c_j x_{ij} \tag{3.1}$$

- c_j is the unit cost per unit in period j.
- x_{ij} is the amount of demand relocated from period j to period i.

Setup Costs: Setup costs are incurred if there is a setup in period i, indicated by the binary variable y_i .

$$\text{Setup Cost } = \sum_{j=1}^{i} s_j y_j \tag{3.2}$$

- s_j is the setup cost for period j.
- y_j is a binary variable indicating a setup in period j (1 if setup occurs, 0 otherwise).

Holding Costs: Holding costs are incurred by holding inventory from earlier periods until it is used to meet the demand in later periods.

$$\text{Holding Cost } = \sum_{i=1}^{n}\sum_{j=1}^{i} h_j x_{ij} \tag{3.3}$$

- h_j is the holding cost per unit per period for period j.
- x_{ij} is the amount of demand relocated from period j to period i.

Combined Objective Function:

$$\text{Minimize } Z = \sum_{i=1}^{n}\sum_{j=1}^{i} c_j x_{ij} + \sum_{j=1}^{i} s_j y_j + \sum_{i=1}^{n}\sum_{j=1}^{i} h_i x_{ij} \tag{3.4}$$

To ensure that solutions remain feasible with respect to real-world limitations, several constraints are imposed:

Demand Satisfaction: The total amount of demand satisfied in each period i, must equal the demand d_i for that period

$$\sum_{j=1}^{i} x_{ij} = d_i \ \forall \mathrm{i} = 1, \dots, \mathrm{n} \tag{3.5}$$

Setup Constraints: Setup constraints ensure that if any amount of demand is met in period i, then a setup cost must be incurred (enforced by y_i).

$$\sum_{j=1}^{i} x_{ij} \leq \mathrm{M} y_i \ \forall \mathrm{i} = 1, \dots, \mathrm{n} \tag{3.6}$$

where M is a sufficiently large number to effectively enforce the constraint.

Pull ahead time window Constraints:

$$x_{ij} = 0 \ \forall i, j \in T \text{ where } i - j > W \tag{3.7}$$

3.2.2 Limitations and suggestions

The basic MILP model, while providing a foundational approach to supply chain reallocation, has several limitations that stem directly from its methodology. Firstly, the model assumes pre-defined demand and costs, which can be unrealistic given the variability in real-world scenarios. Demand can fluctuate due to market trends, seasonal variations, or unexpected events, and unit costs can vary due to factors like inflations. This deterministic approach may lead to solutions that are not robust to real-world variability, potentially resulting in suboptimal performance when faced with unexpected changes. Secondly, the model's focus on a single item type limits its applicability to scenarios where multiple items are managed within the supply chain, as real-world supply chains often involve multiple products with different demand patterns and logistical requirements. Furthermore, the model assumes no cost associated with reallocating items to earlier time periods, which can be unrealistic as reallocations can incur costs due to changes in transportation schedules, additional handling, or other operational adjustments. By understanding these limitations, the development of the model can focus on addressing these issues, potentially through the incorporation of multi-item reallocation capabilities, and improved computational efficiency, thereby making the model more applicable to the complexities of real-world supply chain management**.**

3.3 Enhanced Model

From the previous work shared in section 3.2 that lays down the basic (MILP) model, this chapter continues to work on improving the current basic MILP model. The extended model proposes to consider more aspects of supply chain reallocation, The presence of multiple item types in the system. These enhancements capture the richness and complexity of the contemporary automotive supply chains that are required to consider various products' characteristics, demand volatility, and finite resources over multiple time horizons. This chapter clearly describes the formulation of the enhanced MILP model, the programming of the model via a Python environment and optimization tools, and the testing of the model. This model demonstrates enhancement by comparing the performance of the basic model and determining the extent of the improvements in cost efficiency and resource utilization.

The problem focuses on optimizing the supply chain operations of delivering items to a manufacturing plant over a predefined planning horizon. The initial shipment plan determines the quantity of items to be shipped from supplier to the plant, ensuring that all demand is met within the specified time frames. However, the shipment plan allows for reallocation of quantities to earlier time slots within a defined pull-ahead period, introducing flexibility to adjust for operational constraints. The challenge lies in minimizing the total cost, which includes trucking, setup, holding, and unit costs while adhering to constraints such as truck capacity, time frame limits, and efficient utilization of resources. This problem becomes increasingly complex when considering multiple items, as it requires accounting for item-specific constraints, shared resources, and interactions between items, making it essential to develop an optimization model to address these challenges effectively.

3.3.1 MILP formulation

The decision variables in this model are revised to reflect a more realistic approach that effectively incorporates real world operational constraints.

The variables are defined as follows

- $x_{ijk} \in Z^+$: Integer variable representing the quantity of item k relocated in period j to satisfy demand in period i.
- $Y_j \in \{0,1\}$: Binary variable, 1 if a setup occurs in period j; 0 otherwise.
- $T_{jt} \in \{0,1\}$: Binary variable, 1 if truck t is used in period j; 0 otherwise.

Considering these decision variables, we represent the following parameters where we incurred the trucking cost, unit cost, setup cost and holding cost terms.

- u_{jk}: Unit cost for item k in period j
- C_{jt}: Cost of using truck t in period j
- h_{tk}: Holding cost for item k in period t
- S_j: Setup cost in period j
- d_{ik}: Demand for item k in period i
- V_k: Volume per item of type k
- CV: Capacity of each truck
- M: A large constant
- W: Time window limit

Unit cost**:** This term is derived from the need to minimize the unit cost across periods. The unit cost u_{jk} reflects the cost of unit of product k from period j, and the total cost is calculated by summing over all products and periods. The decision variable x_{ijk} represents the quantity of products relocated, ensuring the model captures the total relocation cost.

$$\text{Unit Cost} = \sum_{k=1}^{K} \sum_{j=1}^{n} u_{jk} \sum_{i=j}^{n} x_{ijk} \tag{3.8}$$

Trucking costs: Truck costs are derived from the operational expense of using trucks for relocation. Each truck has a fixed cost C_{jt} per period, and the binary variable T_{it} indicates whether a truck is used. By summing up all trucks and periods, this term ensures that the model accounts for the total cost of truck usage while optimizing the number of trucks required.

$$\text{Trucking Cost} = \sum_{j=1}^{n} \sum_{t=1}^{T_{max}} C_{jt} T_{it} \tag{3.9}$$

Holding costs: Holding costs are derived from the expense of storing products over time. The cost per unit h_{tk} increases with the duration of storage, and the model sums over all products and periods to capture the total holding cost. This term ensures that the timing of relocations is optimized to minimize storage expenses.

$$\text{Holding Cost} = \sum_{k=1}^{K}\sum_{t=1}^{\mathrm{n}-1} h_{tk} \sum_{i=t+1}^{n}\sum_{j=1}^{\mathrm{t}} x_{ijk} \tag{3.10}$$

Setup costs: Setup costs are derived from the fixed expense of activating a facility for relocation. The cost S_{ik} is incurred only if a setup is active, as indicated by the binary variable Y_{ik}. This term ensures that facilities are only activated when necessary, reducing unnecessary setup costs.

$$\text{Setup Cost} = \sum_{k=1}^{K}\sum_{i=1}^{\mathrm{n}} S_{ik} Y_{ik} \tag{3.11}$$

The combined objective function is

$$\text{Minimize } Z = \sum_{j=1}^{n}\sum_{k=1}^{K} u_{jk} \sum_{i=j}^{n} x_{ijk} + \sum_{j=1}^{n}\sum_{t=1}^{T_{\max}} C_{jt} T_{jt} + \sum_{t=1}^{n-1}\sum_{k=1}^{K} h_{tk} \sum_{i=t+1}^{n}\sum_{j=1}^{\mathrm{t}} x_{ijk} + \sum_{j=1}^{n} S_j Y_j \tag{3.12}$$

To ensure that solutions remain feasible with respect to real-world limitations, several constraints are imposed:

Setup constraints: This constraint is derived from linking the relocation quantity x_{ijk} with the setup decision Y_j. It ensures that products can only be relocated if a facility is active, using a large constant M to enforce this relationship

$$\sum_{i=j}^{n} x_{ijk} \le M \cdot Y_j \ \forall j \in J, k \in K \tag{3.13}$$

This ensures that the relocation quantity x_{ijk} for each item k in each period j can only be positive if there is a setup Y_j in that period.

Demand satisfaction: The demand satisfaction constraint is derived to ensure that the total quantity of products relocated meets the demand d_{ik} for each product and period. This ensures that the model fulfills all customer requirements without over or under-supplying.

$$\sum_{j=1}^{i} x_{ijk} = d_{ik} \ \forall i \in I, k \in K \tag{3.14}$$

This constraint ensures that the total quantity relocated to satisfy demand in each period i for each item k is equal to the demand d_{ik}.

Pull ahead time window constraints: This constraint is derived to enforce a feasible time window (W) for relocations. It ensures that products are not relocated outside the allowable time frame, reflecting practical limitations in scheduling.

$$x_{ijk} = 0 \ \forall i, j \in T, k \in K \text{ where } i - j > W \tag{3.15}$$

Volume capacity constraint: The volume capacity constraint is derived to ensure that the total volume of relocated products does not exceed the combined capacity of the trucks used. By summing up the product volumes V_k and linking them to truck capacity CV, the model ensures that relocations are feasible within the available resources.

$$\sum_{k=1}^{K} V_k \sum_{i=j}^{n} x_{ijk} \leq CV \cdot \sum_{t=1}^{T_{\max}} T_{jt} \ \forall j \in J \tag{3.16}$$

This limits the total volume of items relocated in each period j to the combined capacity of the trucks used in that period.

Truck usage constraint: This constraint is derived to limit the total quantity of items relocated to the combined capacity of the trucks used. It ensures that the number of items moved in each period is within the physical limits of the available trucks.

$$\sum_{k=1}^{K} \sum_{i=j}^{n} x_{ijk} \leq CV \cdot \sum_{t=1}^{T_{\max}} T_{jt} \ \forall j \in J \tag{3.17}$$

This constraint restricts the total number of items relocated in each period j to the combined capacity of the trucks used in that period.

Truck-setup linkage: The truck-setup linkage constraint is derived to ensure that trucks can only be used if a facility setup Y_j is active. This reflects the practical requirement that trucks are only deployed when a facility is operational.

$$T_{jt} \leq Y_j \ \forall j \in J, \forall t \in T \tag{3.18}$$

This ensures that trucks T_{jt} can only be used if there's an active setup in that period ($Y_j = 1$).

Integer and binary constraints:

- $x_{ijk} \in Z^+$: x_{ijk} is a non-negative integer, representing the quantity of items relocated.
- $Y_j \in \{0,1\}$: Y_j is binary, indicating if a setup is active in period j.
- $T_{jt} \in \{0,1\}$: T_{jt} is binary, indicating if truck t is used in period j.

3.3.2 Limitations and suggestions

This improved model effectively managed to lower the total cost and at the same time to meet demand and optimize the resources needed. Due to the consideration of capacity dependence and product specificity, it has good applicability in actual projects.

Despite its improvements, the enhanced model has certain limitations. The added functionality enlarges computing complexity and may have an impact on the product's capability to scale up. As the number of items increases, the total cost (both initial and optimized) increases due to higher relocation and setup costs. Similarly, increasing the number of trucks allowed for better allocation of resources, reducing the optimized total cost. The computational time of the solver increased with the number of items and trucks, reflecting the increased complexity of the optimization problem.

3.4 Enhanced Model with Supplier Integration

Scaling up the model in section 3.3, this model adds supplier integration to the model, an essential dimension of many supply chains that directly affect performance since supplier selection and the allocation of orders are often key decision areas. The proposed supplier integration MILP model aims to optimize supply chain operations by minimizing total costs, including setup costs, holding costs, reallocation costs, supplier costs, trucking costs, and penalties for unused truck space, while satisfying demand and operational constraints.

The proposed model integrates supplier-related parameters into the existing framework, enabling a more comprehensive approach to supply chain optimization. It considers multiple suppliers, products, and time periods, reflecting the complexity of real-world supply chains. The methodology involves solving the model using python and advanced optimization tools, with the outcomes analyzed to demonstrate the benefits of supplier integration. By comparing the results with the baseline model, this chapter highlights the advantages of incorporating supplier dynamics, such as improved cost efficiency, better resource utilization, and enhanced decision-making capabilities. The supplier integration model adds new decision variables, constraints, and objectives into supply chain decisions to reflect supplier decisions.

3.4.1 MILP formulation

The objective function extends the enhanced MILP model by incorporating supplier-related costs, including reallocation costs, unit cost, holding cost, setup cost and penalty costs for unused truck space in this case we consider this by volume. The model is formulated by considering the parameters and decision variables as below

- T: Number of time windows (periods), $i, j = 1, \dots, T$
- S: Number of suppliers, $s = 1, \dots, S$
- w: Pull-ahead time window limit
- K: Number of item types, $k = 1,2, \dots, K$
- R: Number of trucks available for a period
- u_{jks}: Unit cost of item k in period j offered by supplier s
- h_{jk}: holding cost of item k in period j
- b_j: Setup cost in period j (identical for all suppliers)
- l_j: Reallocation cost in period j (identical for all suppliers)
- c_{jrs}: Trucking cost of truck r in period j from supplier s
- d_{jk}: Demand for item k in period i
- V_k: Volume per item of type k

- p_j: Truck usage cost in period j per volume (m^3)
- CV: Capacity of each truck
- M: A large constant

As we see in the previous model, let us update the Decision Variables integrating suppliers

$x_{ijk}^{s's}$: Reallocated amount of item k from period i to j from supplier s' to $s, j < i$

y_j^s: Binary variable, if $x_{ijk}^{s's} > 0, y_j = 1$, otherwise zero

Z_{jrs} : Binary variable, if truck r from supplier s used in j, $z_{jrs} = 1$, otherwise zero

Setup cost: The setup cost term accounts for the fixed expenses incurred when activating a supplier for a specific period. where $b_j$is the setup cost for period j, and y_j^s is a binary variable indicating whether supplier s is active in period j. This term ensures that the model captures the cost of engaging suppliers only when necessary, encouraging efficient supplier selection and minimizing unnecessary activations. The inclusion of this term reflects the practical reality that activating a supplier involves fixed costs, such as administrative or contractual expenses.

$$\text{setup cost} = \sum_{s=1}^{S}\sum_{j=1}^{T} b_j y_j^s \tag{3.19}$$

Holding cost: The holding cost represents the expenses associated with storing inventory over time. where h_{jk} is the holding cost per unit of item k and $x_{ijk}^{s's}$ is the quantity of item k reallocated from supplier s' to s between periods i and j. This term ensures that the model penalizes excessive inventory storage, encouraging timely reallocation and reducing costs associated with prolonged storage, such as warehousing fees or inventory depreciation.

$$\text{Holding cost} = \sum_{s'=1}^{S}\left\{\sum_{k=1}^{k}\left(\sum_{j=1}^{T-1} h_{jk}\sum_{s=1}^{S}\sum_{i=c+1}^{T}\sum_{j=1}^{c} x_{ijk}^{s's}\right)\right\} \tag{3.20}$$

Unit cost: The unit cost term captures the cost of purchasing items from suppliers. where u_{jks} is the unit cost of item k in period j offered by supplier s. This term ensures that the model accounts for the cost of acquiring products from suppliers, which varies depending on the supplier, product type, and time. By minimizing this term, the model selects suppliers and allocates orders in a cost-effective manner.

$$\text{Unit cost} = \sum_{s'=1}^{s}\left\{\sum_{k=1}^{k}\sum_{s=1}^{s}\left(\sum_{j=1}^{T}u_{jks}\sum_{i=j}^{T}x_{ijk}^{s's}\right)\right\} \tag{3.21}$$

Reallocation cost: The reallocation cost term represents the expenses incurred when transferring inventory between facilities or suppliers. where l_i is the reallocation cost in period i, and $x_{ijk}^{s's}$ is the quantity of item k reallocated. This term ensures that the model penalizes unnecessary reallocation, encouraging efficient inventory management and reducing costs associated with inter-facility or inter-supplier transfers.

$$\text{Reallocation cost} = \sum_{s'=1}^{s}\left\{\sum_{k=1}^{k}\sum_{s=1}^{s}\left(\sum_{i=2}^{T}l_i\sum_{j=1}^{i-1}x_{ijk}^{s's}\right)\right\} \tag{3.22}$$

Trucking cost: The trucking cost term accounts for the fixed costs of using trucks for transportation. where c_{jr} is the cost of using truck r in period j, and z_{jrs} is a binary variable indicating whether truck r is used by supplier s in period j. This term ensures that the model captures the cost of transportation and encourages the efficient use of trucks to minimize logistics expenses.

$$\text{Trucking cost} = \sum_{s=1}^{S}\sum_{j=1}^{T}\sum_{r=1}^{R}c_{jr}z_{jrs} \tag{3.23}$$

Penalty cost for unused space in a truck: The penalty cost term addresses the inefficiency of underutilized truck capacity. where p_j is the penalty cost per unit of unused truck volume in period j, CV is the truck capacity, and v_k is the volume of item k. This term ensures that the model penalizes underutilized truck space, encouraging better load planning and maximizing the efficiency of transportation resources.

$$\text{Penalty cost} = \sum_{s'=1}^{s} \left[\sum_{s=1}^{s} \left\{ \sum_{j=1}^{T} p_j \left(CV \sum_{r=1}^{R} z_{jrs} - \sum_{k=1}^{K} \sum_{i=j}^{T} v_k x_{ijk}^{s's} \right) \right\} \right] \tag{3.24}$$

The combined objective function is

Minimize Z=

$$\sum_{s=1}^{s} \sum_{j=1}^{T} b_j y_j^s + \sum_{s'=1}^{S} \left\{ \sum_{k=1}^{k} \left(\sum_{j=1}^{T-1} h_{jk} \sum_{s=1}^{S} \sum_{i=c+1}^{T} \sum_{j=1}^{c} x_{ijk}^{s's} \right) \right\} + \sum_{s'=1}^{s} \left\{ \sum_{k=1}^{k} \sum_{s=1}^{s} \left(\sum_{j=1}^{T} u_{jks} \sum_{i=j}^{T} x_{ijk}^{s's} \right) \right\}$$
$$+ \sum_{s'=1}^{s} \left\{ \sum_{k=1}^{k} \sum_{s=1}^{s} \left(\sum_{i=2}^{T} l_i \sum_{j=1}^{i-1} x_{ijk}^{s's} \right) \right\} + \sum_{s=1}^{S} \sum_{j=1}^{T} \sum_{r=1}^{R} c_{jr} z_{jrs}$$
$$+ \sum_{s'=1}^{s} \left[\sum_{s=1}^{s} \left\{ \sum_{j=1}^{T} p_j \left(CV \sum_{r=1}^{R} z_{jrs} - \sum_{k=1}^{K} \sum_{i=j}^{T} v_k x_{ijk}^{s's} \right) \right\} \right] \tag{3.25}$$

To ensure that solutions remain feasible with respect to real-world limitations, constraints are modified as follows:

Modified demand constraint: This constraint ensures that the total quantity of item k reallocated across all suppliers and periods satisfies the demand d_{ik} for that item in each period i. This constraint is critical for maintaining supply chain balance, as it guarantees that customer or production demands are met without over or under supplying. By enforcing this equality, the model ensures that the supply chain operates efficiently and avoids shortages or excess inventory

$$\sum_{s'=1}^{s} \left(\sum_{s=1}^{s} \sum_{j=1}^{i} x_{ijk}^{s's} \right) = d_{ik} \ \ \forall i = 1, \dots, T, k = 1, \dots, K \tag{3.26}$$

Modified setup constraint: This constraint links the reallocation decision to the activation of suppliers. The binary variable y_j^s indicates whether supplier s is active in period j. If y_j^s=0 the constraint ensures that no reallocation $x_{ijk}^{s's}$ can occur for that supplier in that period. The large constant M acts as an upper bound, allowing reallocation only when the supplier is active. This constraint prevents unnecessary supplier activations, reducing setup costs and ensuring that suppliers are only engaged when required. It reflects the practical reality that supplier activation involves fixed costs and operational overhead, which should be minimized.

$$\sum_{s=1}^{S}\left(\sum_{k=1}^{K}\sum_{i=j}^{T} x_{ijk}^{s's}\right) \leq M y_j^s \;\; \forall j = 1, \dots, T, s' = 1, \dots, S \tag{3.27}$$

Modified trucking constraint: This constraint ensures that the total volume of items transported in each period does not exceed the combined capacity of the trucks used. The term v_k represents the volume of item k, and CV is the capacity of each truck. The binary variable z_{jrs}indicates whether truck *r* is used by supplier *s* in period *j*. By summing up all trucks, the model ensures that the total volume of items reallocated is within the available truck capacity. This constraint is essential for maintaining logistical feasibility, as it prevents overloading and ensures that transportation resources are utilized efficiently.

$$\sum_{s'=1}^{S}\left(\sum_{k=1}^{K} v_k \sum_{i=j}^{T} x_{ijk}^{s's}\right) \leq CV \sum_{r=1}^{R} z_{jrs} \;\; \forall j = 1, \dots, T, s = 1, \dots, S \tag{3.28}$$

Pull-ahead time window limit constraints: This constraint enforces a pull-ahead time window limit, ensuring that items are not reallocated outside a specified time frame. The parameter *w* defines the maximum allowable time difference between the source period *j* and the destination period *i*. If $i - j > w$, the reallocation quantity $x_{ijk}^{s's}$ is forced to zero.

$$x_{ijk}^{s's} = 0 \;\; \forall i, j = 1, \dots, T, k = 1, \dots, K, s', s = 1, \dots, S, i - j \leq w \tag{3.29}$$

Additional integer and binary constraints

- $x_{ijk}^{s's} \in Z^+$: This constraint ensures that the quantity of items *k* reallocated from supplier s' to supplier *s* between periods *j* and *i* must be a non-negative integer.
- $Z_{jrs} \in \{0,1\}$: This binary variable equals 1, if truck *r* is used by supplier *s* in period *j*. otherwise, it is 0.
- $y_j^s \in \{0,1\}$: This binary variable equals 1, if supplier *s* is activated (i.e., used for supplying items) in period *j*.

3.4.2. Limitations and suggestions

While the proposed supplier-integrated MILP model offers a comprehensive framework for optimizing supply chain operations by incorporating supplier dynamics, it is not without limitations. One major challenge lies in its computational complexity, as the inclusion of multiple suppliers, items, and time periods significantly increases the number of integer and binary variables, making the model less scalable for large networks. Additionally, the model assumes all parameters such as costs, demands, and capacities must be known and fixed in advance, which limits its applicability in dynamic or uncertain environments. The trucking component is simplified and does not account for routing, geographic constraints, or multi-drop deliveries, while cost functions are linear, ignoring real-world pricing structures like bulk discounts or tiered logistics fees. Furthermore, the model lacks support for multi-layered supply chains, and it treats all supplier setup costs as identical, which may oversimplify real-world scenarios where onboarding costs vary. To address these issues, future extensions could incorporate heuristic algorithms for scalability and use stochastic optimization to handle uncertainties in demand and supply. Additionally, incorporating dynamic replanning mechanisms and supplier-specific attributes would make the model more adaptive and better aligned with real-world supply chain complexities.

CHAPTER 4: EXPERIMENTATION AND RESULTS

4.1 Overview

This chapter presents the results obtained from the implementation of the optimization models discussed in Chapter 3. The focus is on evaluating the performance of the basic, enhanced, and supplier-integrated (MILP) models in addressing supply chain reallocation challenges. The analysis includes a detailed comparison of the model's outcomes in terms of cost efficiency, resource utilization, and demand satisfaction. By applying these models to real-world scenarios, this chapter aims to highlight their practical applicability and effectiveness in optimizing supply chain operations.

The analysis highlights the strengths and weaknesses of each model. Key factors like total cost savings, setup efficiency, and inventory holding costs are examined to understand how well the models handle the complexities of supply chain operations. We also explore how different parameters, such as changes in demand, truck capacity, and supplier integration, affect the performance of the models. This helps to provide a clearer picture of the trade-offs involved in optimizing supply chains and point out areas where the models can be improved.

Additionally, we discuss some of the challenges faced during the implementation of these models, especially with the enhanced and supplier-integrated versions. While these advanced models offer more flexibility and accuracy, they also require more computational resources and time to solve. This section emphasizes the importance of finding a balance between making the models more sophisticated and ensuring they remain practical for real-world use. These ideas aim to refine the models further and make them more adaptable to the dynamic and complex nature of modern supply chains

4.2 Implementation of the Model

The optimization models are implemented using a systematic approach, to evaluate the performance of these models, multiple instances with synthetic data sets are considered. Every model ensures that demand is met in each period while adhering to operational constraints.

Each period has specific demand requirements, and the model allows for the reallocation of demand from one period to another, provided it satisfies the constraints. The MILP model is solved in a Python environment because this is a very flexible and extendable tool in solving combinatorial optimization problems. PuLP solver, which is used to solve linear programming problems, is used in the construction of the model as well as to solve the problem. The decision variables, the objective function, and the constraints of the problem are formulated based on the PuLP modeling language. As a boasting solver, PuLP can solve large-size problems with multiple variables and constraints as a MILP problem which suits this study. The optimization results are visualized using Python libraries, specifically Matplotlib, to generate analytical plots that illustrate cost trends, resource utilization, and model performance metrics.

4.3 Results of basic model

The results of 3.2 Basic Model3.2 Basic Model highlight its effectiveness in optimizing the supply chain for a single item type over a planning horizon of 5,10,15,20,25,30 and 35 time periods. Considering random instances for all parameters(c_j, s_i, h_i) ranging between 1-10 to reduce the complexity we conducted multiple tests where it was found that for every test the solver gave a better optimal solution than the initial cost. Below, the key findings are discussed in detail.

Table 4.1 Test settings for basic MILP model

Test Set	A (Time Periods)	B (Items)	C (Time Windows)
T-1	5	1	5
T-2	10	1	5
T-3	10	1	10
T-4	15	1	5
T-5	15	1	10
T-6	20	1	5
T-7	20	1	10
T-8	25	1	5
T-9	25	1	10
T-10	30	1	5
T-11	30	1	10
T-12	35	1	5

Table 4.1 displays the test settings for the basic MILP model where each test set (T-1 through T-13) is constructed using a unique combination of three parameters: A (number of time periods),

B (number of items), and C (number of allowable time windows). The primary goal is to examine the scalability and performance of the proposed MILP model under increasing temporal complexity and varying time window constraints.

- Parameter A (Time Periods) increases gradually from 5 to 35, representing small to large-scale planning horizons.
- Parameter C (Time Windows) alternates between 5 and 10 to simulate different levels of delivery flexibility and constraint tightness.
- Parameter B (Items) is fixed at 1 throughout all test sets to isolate the effects of A and C on model performance.

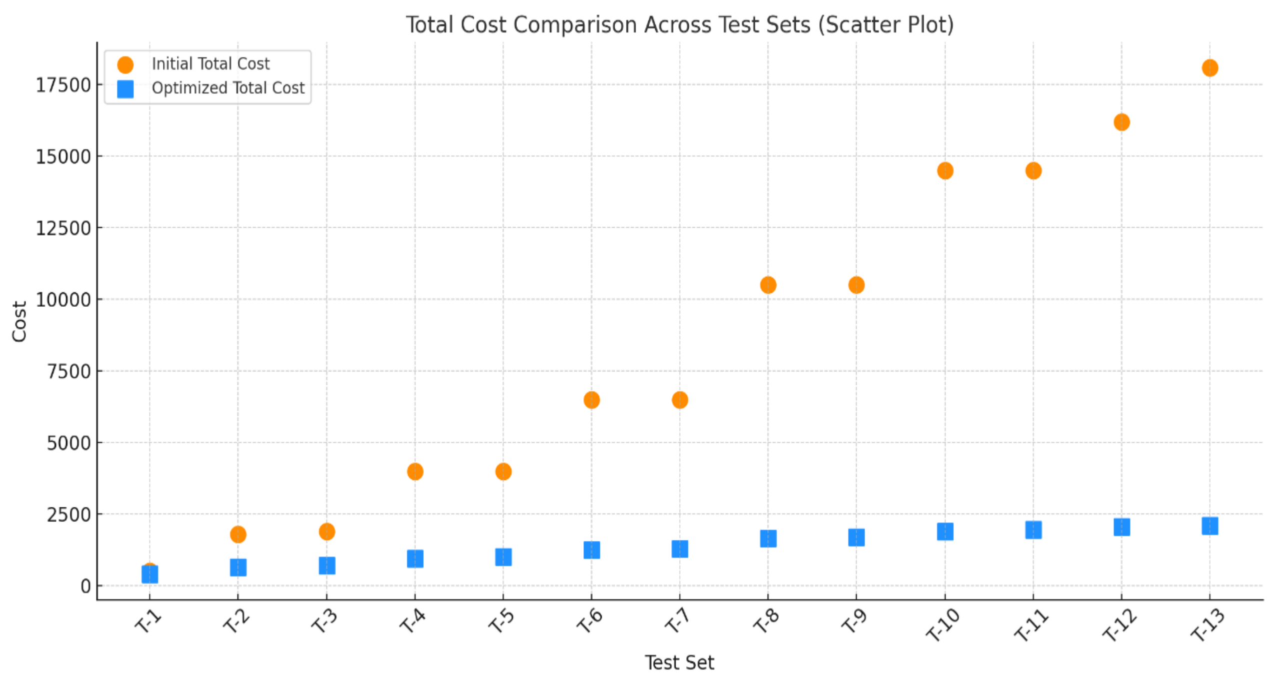

Figure 4.1: Initial Costs Vs Optimal Costs

Figure 4.1 illustrates a clear comparison between the initial total cost and the optimized total cost across thirteen test scenarios (T-1 to T-13). An upward trend is observed in the initial costs, indicating increasing inefficiency as the complexity of test sets grows. In contrast, the optimized costs remain relatively stable, highlighting the effectiveness of the proposed MILP models in maintaining cost efficiency regardless of scale.

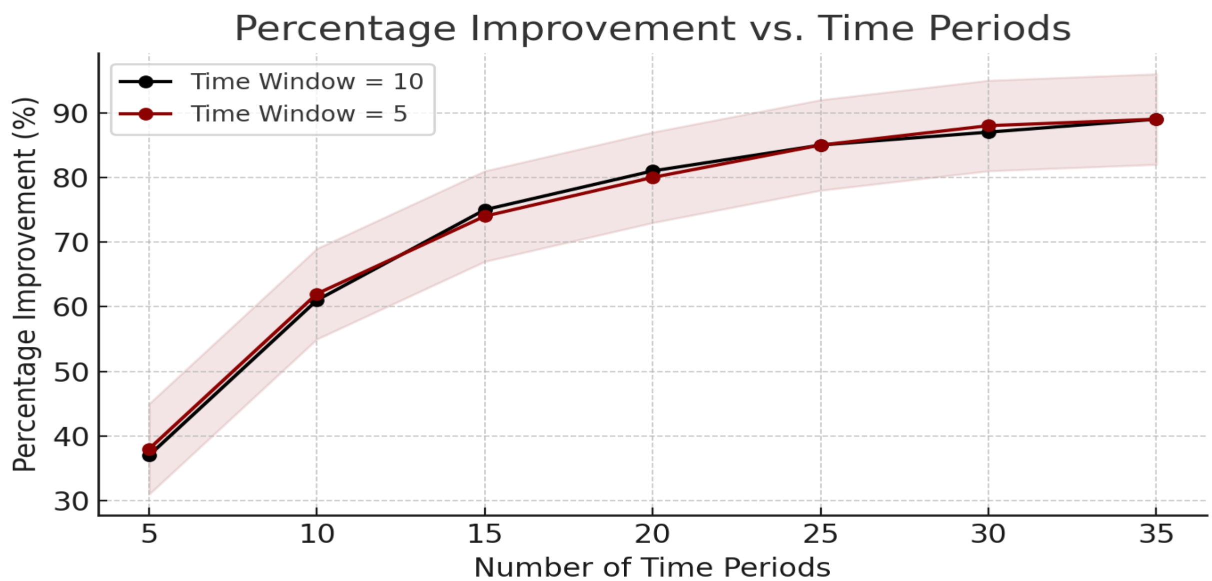

Figure 4.2: Percentage improvement Vs Time periods

Figure 4.2 shows a clear positive relationship between the number of time periods and the percentage improvement in logistics cost. As the number of periods increases, the optimization model becomes more effective. Overall, the trend highlights that increasing the number of available time periods and allowing greater reallocation flexibility significantly boosts the model's ability to reduce costs.

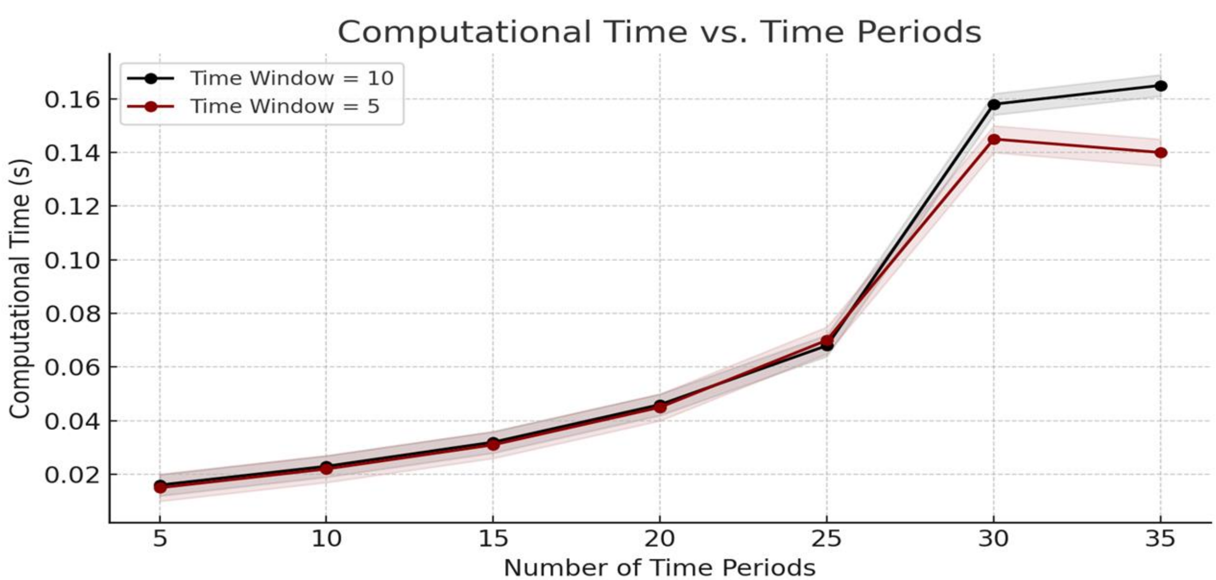

Figure 4.3 Computational Time Vs Time periods

Figure 4.3 displays the relationship between computational time and the number of time periods, evaluated for two different time windows (5 and 10). As expected, the computational time increases with the number of time periods, reflecting the expanding solution space and increasing complexity. However, an unexpected drop in average solve time is observed between 30 and 35 time periods. This observation, while statistically marginal, was based on five instances per time period, which may not be sufficient to draw a robust conclusion.

One possible reason for this drop is that certain structural patterns in the T=35 instances made the MILP problem more tractable — for example, by increasing scheduling flexibility or allowing the solver to prune infeasible branches more efficiently. Another possibility is that solver heuristics incidentally converged faster on these specific instances

In contrast, the optimized plan reduced the number of setups and balanced inventory levels across the planning horizon. This led to a significant overall cost reduction, demonstrating the model's ability to generate cost-efficient solutions. The model made effective use of the pull-ahead period, which allowed items to be shifted to earlier time periods within a predefined window. This reallocation strategy played a key role in reducing holding costs. The results showed that most reallocations occurred within the immediate pull-ahead window, ensuring that demand is met without creating excessive inventory in earlier periods. The reallocation process is carefully balanced to avoid unnecessary setups, which further contributed to cost savings.

The model is computationally efficient, solving all test instances within a fraction of seconds. Computational time varied depending on the complexity of the demand patterns and the initial shipment plan, but it consistently demonstrated scalability for the 35-period planning horizon. This indicates that the model can handle larger planning horizons or more complex scenarios in future applications.

4.4 Results of Enhanced Model

This section presents the results of the enhanced MILP model, comparing its performance with the basic MILP model in optimizing supply chain logistics. The improvements in cost efficiency, demand satisfaction, and resource utilization are analyzed through computational experiments. The enhanced model introduces a refined optimization framework that addresses the limitations of the basic model by incorporating multi-item dependencies, truck utilization constraints, and dynamic reallocation strategies. This model effectively enhances cost efficiency, demand fulfillment, and resource utilization while maintaining feasible computational complexity.

In this study, twenty test sets (T-1 to T-20) are constructed to evaluate the scalability and performance of the proposed MILP model for supply chain reallocation in the automotive industry. The experimental design includes four parameters: A (Number of Items), B (Number of Time Periods), C (Number of Allowable Time Windows), and D (Number of Trucks).

The experiment is conducted for a fixed number of time periods (T = 35) and varying numbers of items K and trucks T_max. Here the data we considered for all parameters (u_{jk}, C_{jt}, h_{tk} ,S_j,d_{ik})are random synthetic data ranging between 1-50 for conducting experiments. Truck capacity CV is set to 100 and a large constant M. For each combination of items and trucks, 5 random test instances are generated. The initial total cost is calculated by assuming all demands are satisfied in the same period they occurred, with no holding costs.

Table 4.2 Test settings for enhanced MILP model

A (Items)	D = 10	D = 20	D = 30	D = 40	D = 50
1	T-1	T-2	T-3	T-4	T-5
10	T-6	T-7	T-8	T-9	T-10
15	T-11	T-12	T-13	T-14	T-15
25	T-16	T-17	T-18	T-19	T-20

Table 4.2 displays the test settings for the enhanced MILP model to ensure consistency in temporal structure and scheduling flexibility, the parameters B and C are fixed across all test sets: B=35 and C=10. The focus of the test design is on varying two parameters:

- A – Number of Items: Values tested are A = 1, 10, 15, 25. Increasing A increases the dimensionality and size of the optimization problem, allowing analysis of the model’s behavior under increased workload and problem scale.

- D – Number of Trucks: Values tested are D = 10, 20, 30, 40, 50. Changing D simulates varying levels of transport resource availability, influencing the feasibility and distribution strategies within the model.

By maintaining B and C constant, the experiment isolates the effect of increasing problem scale and logistic support. This enables an in-depth evaluation of the MILP model's scalability, cost-efficiency, and adaptability under changing operational constraints

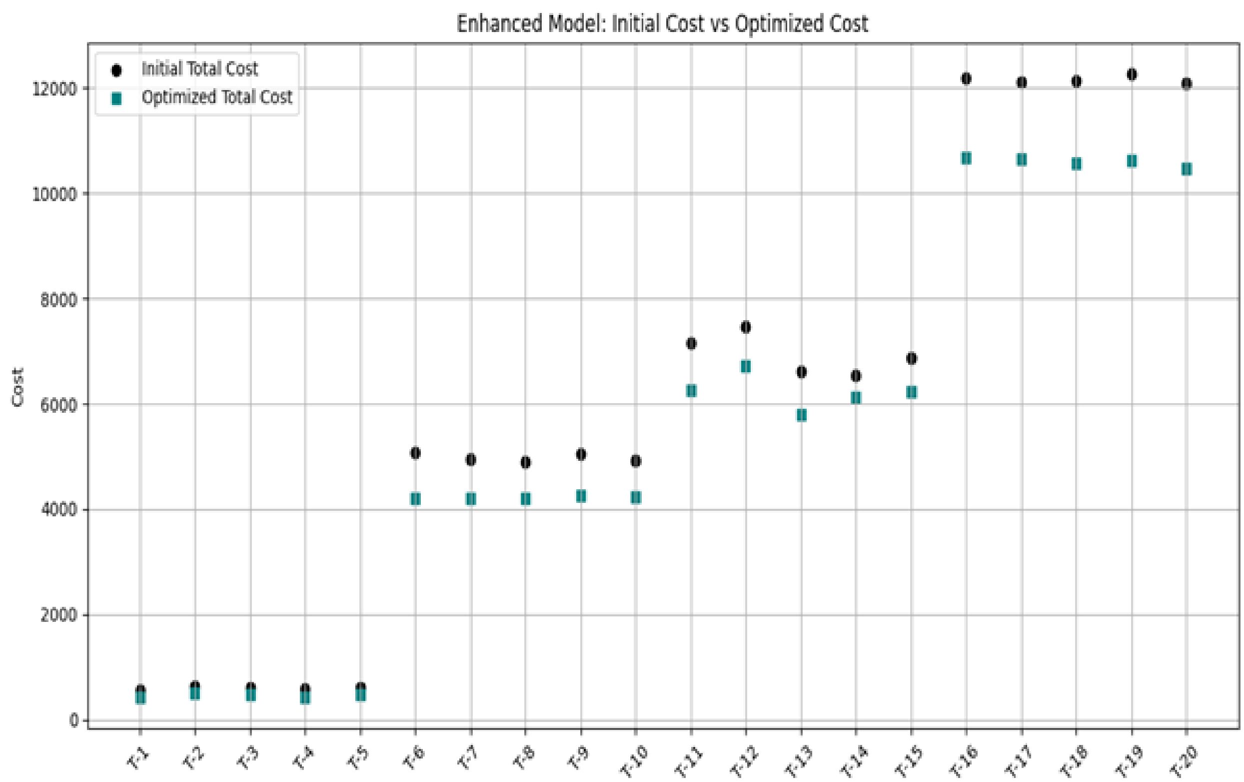

Figure 4.4 Enhanced model Initial Vs Optimized Total Costs

Figure 4.4 compares initial and optimized total costs across 20 test sets (T-1 to T-20), showing a consistent cost-saving trend after optimization. In each test case, the optimized cost is visibly lower than the initial cost, with the gap becoming more pronounced in higher-cost scenarios (from T-11 onward).

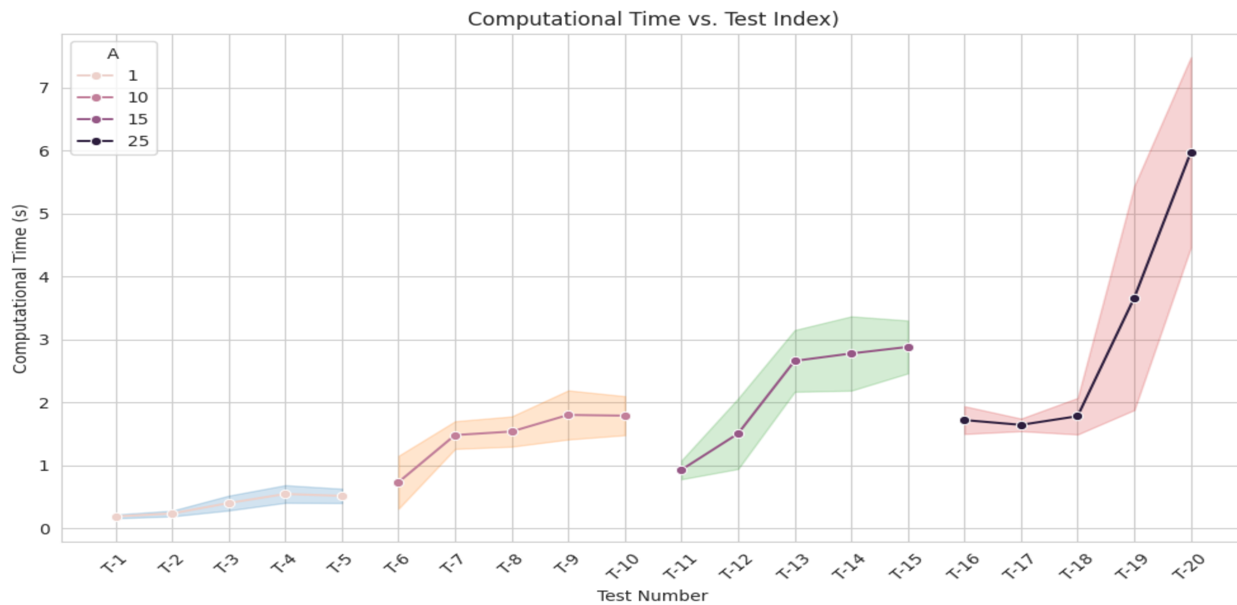

Figure 4.5 Enhanced model Computational Times Vs Test Index

Figure 4.5 illustrates the computational time (in seconds) across varying values of parameter **A** (1, 10, 15, and 25). As parameter **A** increases, there is a general upward trend in computational time. In contrast, for smaller values of **A**, the computational time remains relatively low and stable. This suggests that the computational time escalates more sharply in later tests when **A** is large, potentially due to increased data complexity or algorithmic demand.

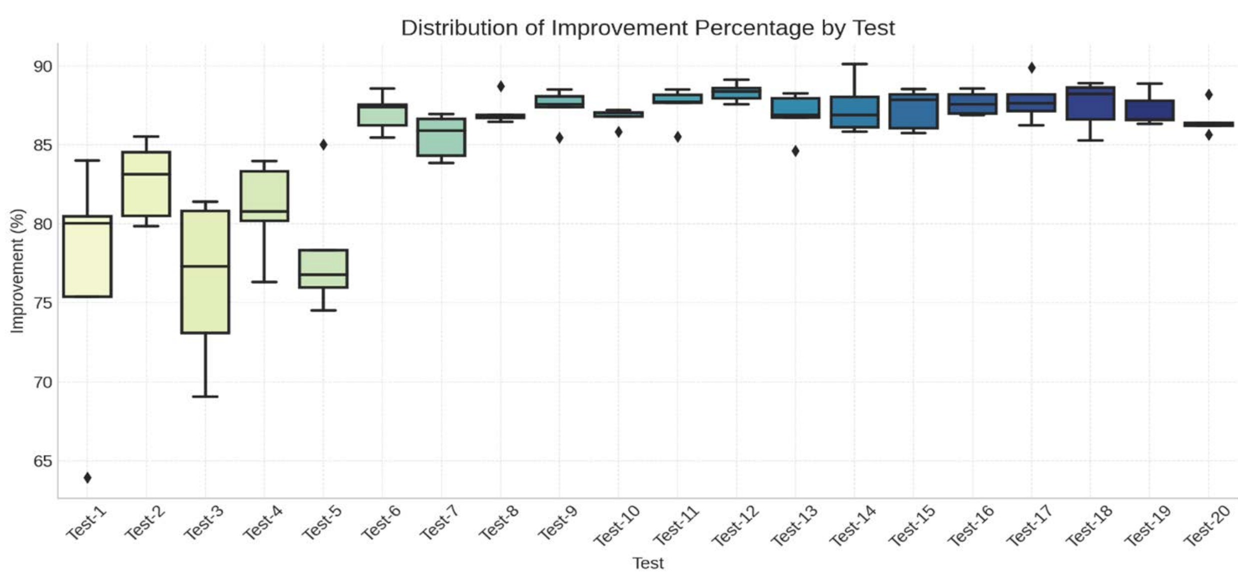

Figure 4.6 Enhanced model Percentage (%) Improvement Distribution

Figure 4.6 visualizes the distribution of improvement percentages across 20 different tests (T-1 to T-20). Each box represents the improvement scores for a specific test, with the central line indicating the median and the whiskers showing variability outside the upper and lower quartiles. Outliers are marked as individual points. The plot reveals a noticeable upward trend in median improvement percentages from early to later tests suggesting that performance becomes more stable and optimized as testing progresses.

The significant improvement of nearly 90% observed in several instances of the enhanced MILP model stems from the contrast between a naive initial plan and a highly optimized allocation strategy. The initial total cost is computed under the assumption that all demands are satisfied in the same period they occur, without any consolidation, reallocation, or cost-saving measures effectively representing a worst-case scenario in logistics planning. In contrast, the optimized plan leverages the full capabilities of the MILP formulation, which includes temporal reallocation of items, joint delivery through truck capacity maximization, setup cost minimization, and intelligent activation of suppliers. These mechanisms lead to much more efficient use of resources, dramatically reducing costs. Thus, the nearly 90% improvement does not imply that real-world systems are currently operating at such inefficiencies, but rather that the baseline used is intentionally simplistic to illustrate the full potential of the optimization model under idealized, controlled conditions.

Unlike the basic model, which focuses on unit, setup, and holding costs in a simplified manner, the enhanced model integrates trucking costs. This addition leads to a more realistic representation of supply chain logistics, resulting in a more balanced cost distribution. Furthermore, improved truck utilization minimizes transportation costs by ensuring that shipments are consolidated efficiently, reducing the number of underutilized trucks in operation.

By incorporating truck constraints and volume capacity limitations the model optimizes transportation logistics. This improvement translates into lower operational costs and a more sustainable use of transportation resources. The model effectively reduces wasted capacity, ensuring that shipments are consolidated and routed efficiently, which is especially beneficial for large-scale supply chain operations. The introduction of multi-item dependencies and truck constraints increases the number of decision variables and constraints, leading to a moderate rise in computation time. However, this added complexity is justified by the significant cost savings and operational efficiency improvements

4.5 Results of Supplier-Integrated Model

The supplier-integrated MILP model represents the most advanced version of the optimization framework, extending the previous enhanced model by integrating supplier-related constraints, costs, and decision variables. The addition of supplier selection, reallocation costs, and penalties for underutilized truck space allows for a more realistic and adaptable representation of supply chain logistics. By considering multiple suppliers, their associated costs, and the efficient distribution of orders, this model significantly enhances cost efficiency and transportation utilization.

In this study, a series of test scenarios are developed to evaluate the effectiveness of this MILP approach. Each test set is constructed based on five core parameters: the number of suppliers (*A*), number of items (*B*), number of time periods (*C*), number of available trucks (*D*), and the pull-ahead time window (*E*). The tests are carefully designed to incrementally increase the complexity of the supply chain problem by varying the number of suppliers and items, while keeping the time horizon (C = 35 periods), logistics resources (D = 10 trucks), and delivery flexibility (E = 25 pull ahead time) constant across all scenarios.

The objective is to understand how the MILP model performs under varying problem sizes, especially in terms of cost reduction and computational efficiency. **Table 4.3** displays the test settings for supplier integrated MILP model and each configuration, three instances with random data for all parameters $(u_{jks}, h_{jk}, b_j, l_j, c_{jrs}, d_{jk}, p_j)$ ranging between 1-50 are run, and key cost parameters are measured before and after optimization. The total cost, both pre and post optimization, is calculated as the sum of these components. Additionally, the percentage improvement and computational time in seconds are recorded to assess the optimization's effectiveness and scalability.

Table 4.3 Test Settings for supplier- integrated MILP model

Test Set	A (Suppliers)	B (Items)
T-1	1	1
T-2	1	5
T-3	1	10
T-4	1	15
T-5	1	25
T-6	2	1
T-7	2	5
T-8	2	10
T-9	2	15
T-10	2	25
T-11	3	1
T-12	3	5
T-13	3	10
T-14	3	15
T-15	3	25

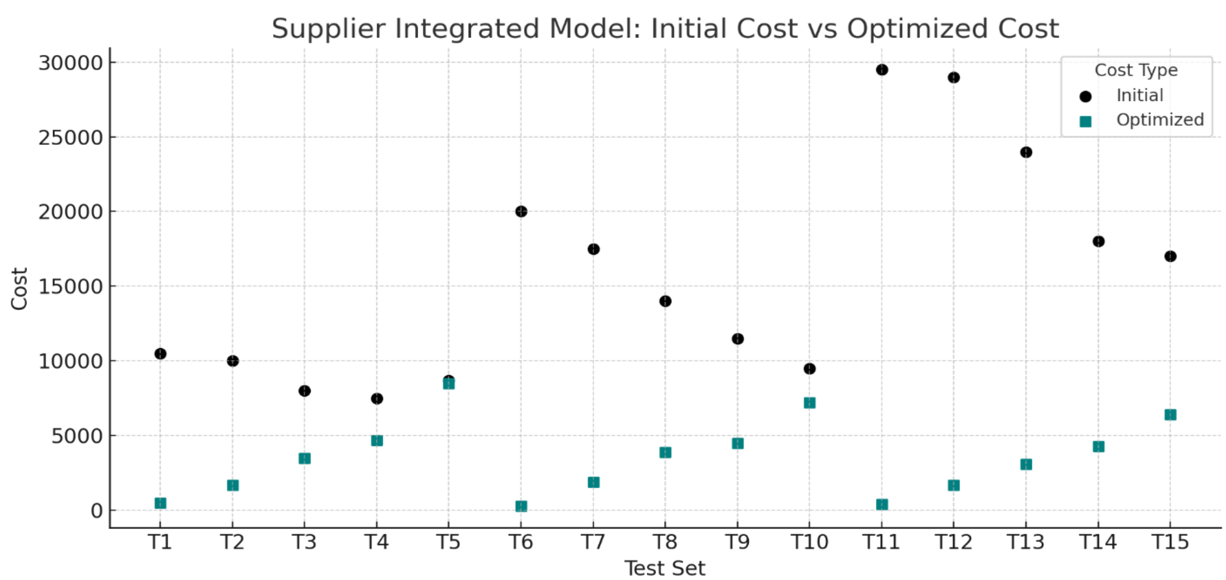

Figure 4.7 Supplier Integrated model Initial Cost vs Optimized Cost

Figure 4.7 illustrates the total cost behavior across all test sets, showcasing both initial and optimized costs at the instance level. Each test set (T-1 to T-15) represents a distinct configuration based on supplier and item parameters. A consistent and significant reduction in total cost is observed after applying the MILP optimization, demonstrating the model's effectiveness. The visual spread also emphasizes the optimization across different problem sizes and conditions.

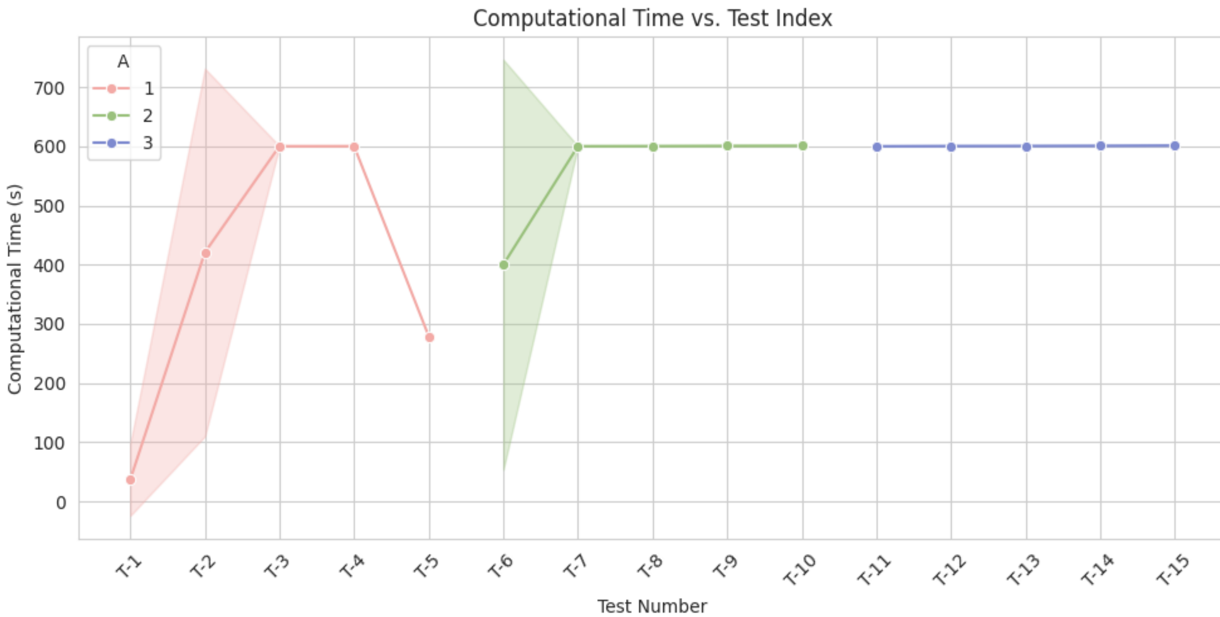

Figure 4.8 Supplier Integrated model Computational time Vs Test index

Figure 4.8 presents the variation in computational time across different test sets (T-1 to T-15), grouped by the number of suppliers (A = 1, 2, and 3). This trend indicates that as supplier count increases, the MILP solver approaches its time ceiling, reinforcing the computational intensity of multi-supplier configurations and the need for scalable optimization strategies.

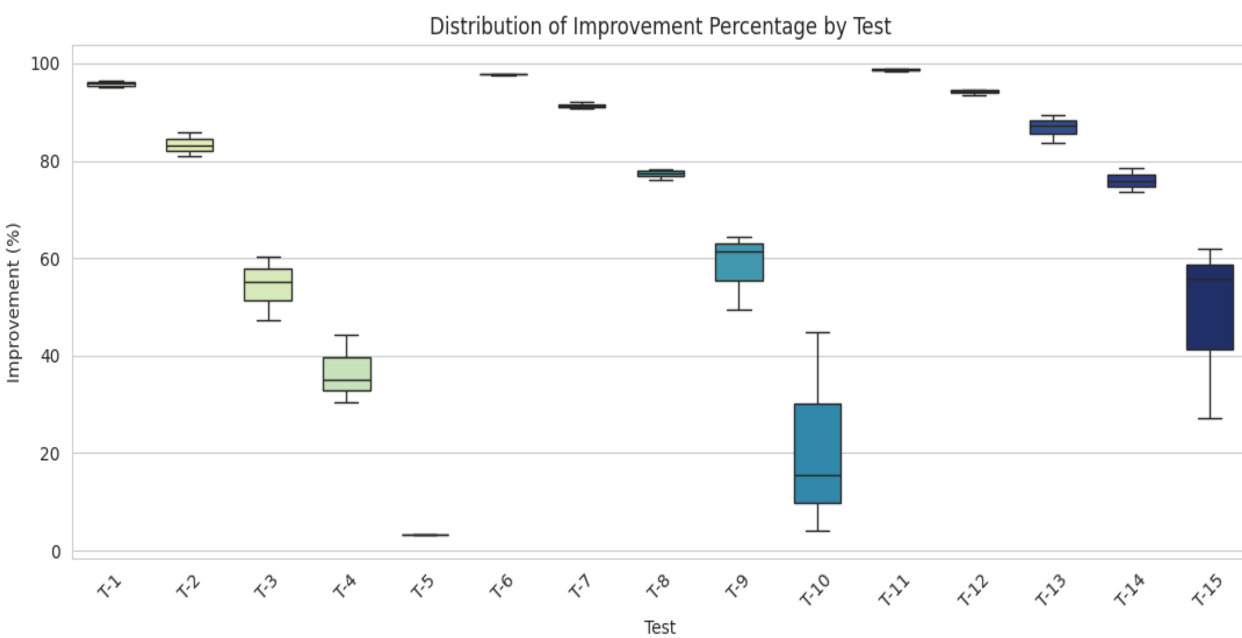

Figure 4.9 Supplier Integrated model Percentage (%) Improvement Distribution

Figure 4.9 illustrates the distribution of percentage improvement across all test sets (T-1 to T-15), highlighting the consistency and variability of the optimization results. Each box represents the spread of improvement values among multiple instances within a test, while the lines (whiskers) show the range, and any outliers are indicated individually.

The results show a significant reduction in overall supply chain costs, primarily driven by better supplier selection, more effective truck utilization, and optimized shipment reallocation strategies. The introduction of penalties for underutilized truck space ensures that shipments are consolidated more efficiently, thereby lowering total trucking costs. Additionally, the model incorporates reallocation cost constraints, which prevent excessive movement of inventory between suppliers unless it is cost-effective.

However, as expected, the computational time tended to rise with problem complexity, especially in instances with higher item counts. Unlike the basic model, which does not consider truck utilization, and the enhanced model, which optimizes transportation costs based on demand, the supplier-integrated model ensures that trucks are utilized efficiently across multiple suppliers and shipment periods. The following results demonstrate how the supplier-integrated model outperforms both the basic and enhanced models, highlighting improvements in total supply chain costs, supplier allocation efficiency, and truck utilization.

4.6 Comparative Analysis

In this section, a comparative analysis is presented to evaluate the performance of the three MILP models based on key metrics such as cost efficiency, truck utilization, computational complexity, and scalability. Each model introduces new constraints and decision variables to improve supply chain optimization, leading to progressive advancements in overall performance.

The basic model serves as the foundational framework for supply chain reallocation, focusing on minimizing unit costs, setup costs, and holding costs while ensuring demand fulfillment. However, it does not account for truck utilization or supplier selection, leading to inefficient resource allocation and higher operational expenses. The enhanced model builds on this by introducing truck constraints and time-window-based shipment reallocation, allowing for better cost optimization and improved demand fulfillment. However, it still lacks supplier-related constraints, which limits its adaptability in complex multi-supplier environments.

The supplier-integrated MILP model further advances the optimization framework by integrating supplier selection, reallocation costs, and penalties for underutilized truck space. This model effectively reduces overall costs, enhances order reallocation flexibility, and ensures optimal truck utilization, making it the most comprehensive and efficient approach among the three. However, the increase in constraints and decision variables results in higher computational complexity, requiring more processing power to generate optimal solutions.

Compared to existing models in the literature, the models proposed in this thesis offer a unique level of integration and operational realism. While earlier works such as Guerrero et al. [39] and Fontaine et al. [41] address specific logistics challenges such as vehicle routing or truck utilization, most of them do so in isolation. This thesis advances the field by developing a progressive modeling framework that incorporates three critical dimensions:

- reallocation of deliveries across fixed time slots
- truck volume utilization and associated cost penalties and
- Supplier activation decisions with setup cost modeling.

Unlike traditional models that assume uniform delivery patterns or focus on static routing, the proposed MILP models allow slot-level, multi-item and multi-supplier planning under deterministic constraints [43] [46] [54]. This adds both practical flexibility and computational transparency. However, the models are limited by their deterministic assumption, they do not currently handle uncertainty in demand or disruptions, as seen in stochastic or robust optimization models [36] [45]. Additionally, while the models are scalable for mid-sized instances, solving very large networks may require advanced solvers (e.g., Gurobi) or decomposition techniques [65]. Despite these constraints, the modularity of the framework allows it to be adapted and extended for real-world logistics environments.

The following **Table 4.4** provides a detailed comparison of the three models, highlighting their strengths, weaknesses, and practical applications in different supply chain environments.

The proposed MILP-based reallocation models demonstrate that shipment plans can be effectively optimized within a deterministic environment, significantly reducing logistics costs without missing delivery targets. By integrating setup costs, truck usage penalties, and supplier activation constraints, the models reveal that considering vehicle and supplier-level parameters in reallocation decisions leads to superior cost performance compared to traditional static schedules. Furthermore, the extended models show that supplier selection and time-slot reallocation together improve both efficiency and flexibility, enabling logistics managers to handle complex delivery networks more intelligently. Computational results confirm that the models scale reasonably well and can accommodate large, multi-item, multi-supplier scenarios, suggesting practical applicability in high-frequency environments such as automotive manufacturing. Overall, the research highlights that data-driven reallocation models can support more strategic delivery planning, providing cost savings and operational resilience even in the absence of uncertainty.

Table 4.4 Comparative analysis among proposed models

Dimension	**Basic Model**	**Enhanced Model**	**Supplier-Integrated MILP Model**
Model Complexity	Simplest structure; single item and supplier; no truck logic.	Moderate: Includes truck constraints, multi-item handling.	Highly complex; includes suppliers, truck utilization, and penalty for unused space.
Objective Function Components	Unit cost, setup cost, holding cost.	Adds trucking cost.	Adds supplier cost, reallocation cost, and penalty for unused truck volume.
Real-World Relevance	Limited; ideal for small or controlled environments.	Good for mid-sized operations with delivery fleets.	Best for real-world supply chains with multi-supplier dynamics.
Scalability	High; quick solve time.	Moderate; computing time increases with items and trucks.	Lower; computing time increases significantly with complexity.
Applicability	Academic or early-stage modeling.	Factory or warehouse logistics.	Industrial-grade supply chains with suppliers and trucks.
Key Limitations	No multi-item/truck/supplier logic.	Lacks supplier dynamics.	Most computationally intensive.

CHAPTER 5: CONCLUSION AND FUTURE RESEARCH

This thesis sets out to address inefficiencies in slot-based delivery planning within the automotive supply chain by proposing a structured reallocation framework using MILP. Across a progressive suite of three optimization models, the basic, enhanced, and supplier-integrated MILP models. This study successfully demonstrated that proactive, deterministic reallocation of shipments leads to measurable cost savings, better truck utilization, and improved scheduling efficiency.

The basic model validated the concept that even a single-item, single-supplier delivery plan can be significantly improved by reallocating shipments within a pull-ahead time window. The model minimized holding and setup costs through simple rebalancing logic, resulting in smoother demand distribution and a clear reduction in fragmented deliveries.

Building on this, the enhanced model introduced truck utilization constraints and multi-item scenarios. This inclusion addressed one of the most persistent operational issues in automotive logistics: the dispatch of underutilized trucks. The model accounted for both volume-based constraints and truck activation costs, revealing that consolidation across time slots reduced total logistics costs without compromising demand fulfillment. The results showed a notable drop in setup frequency and unit delivery cost, emphasizing the value of bundling deliveries within feasible capacity thresholds.

The supplier-integrated model further enhanced realism by incorporating multiple suppliers, supplier-specific constraints. This layer brought the optimization closer to real-world application by addressing not just transportation costs but also supplier setup penalties and inter-supplier dependencies. The results illustrated that intelligent supplier engagement selecting when and which supplier should fulfill an order enabled better cost-performance outcomes. More importantly, this model provided operational insights into how logistics managers can strategically deactivate or engage suppliers to minimize total expenditure while maintaining service levels.

This thesis provides a structured methodology for mid-horizon logistics planning distinct from traditional disruption-based or heuristic scheduling methods. It fills a vital research gap by integrating deterministic reallocation, truck optimization, and supplier logic into a unified MILP framework. The modular nature of the models offers flexibility for implementation in various operational contexts from small-scale suppliers to large OEM networks. While the models performed well under deterministic assumptions, real-world logistics systems often face stochastic elements such as demand uncertainty, traffic delays, and production disruptions.

However, it is important to note that this research serves as a prototype framework, and its performance has been tested using synthetic datasets composed of small-scale, numerically simplified instances designed to validate model logic and structure. While these controlled experiments help illustrate the core benefits of reallocation and integrated planning, they do not fully capture the complexities of live industrial data, including large-scale variability, uncertainty, and real-time constraints. Therefore, the models presented should be viewed as foundational tools rather than final, deployable systems. Future research should focus on scaling the models for industrial-scale datasets, incorporating stochastic elements such as variable demand or lead times, and integrating real-time decision-making to enhance practical applicability. Moreover, refining the models to support multi-level logistics, nonlinear cost structures, and dynamic supplier behavior would significantly enhance their operational relevance and adaptability to complex supply chain networks.

APPENDIX

Basic model experiment results

Instance	Initial Unit Cost	Initial Setup Cost	Initial Holding Cost	Initial Total Cost	Opt. Unit Cost	Opt Setup Cost	Opt Holding Cost	Opt Total Cost	Percentage Improvement (%)	Computational Time (s)
TEST-1 {5, 1, 5}										
1	432	23	267	722	227	3	128	358	50.42	0.05
2	363	30	331	724	174	2	151	327	54.83	0.03
3	49	22	76	147	52	2	94	148	-0.68	0.03
4	213	22	173	408	156	1	156	313	23.28	0.03
5	186	32	184	402	164	7	188	359	10.70	0.01
6	312	21	153	486	155	1	119	275	43.42	0.01
7	323	34	256	613	162	1	150	313	48.94	0.02
8	136	31	174	341	107	2	108	217	36.36	0.02
9	212	36	248	496	167	5	137	309	37.70	0.04
10	343	21	389	753	184	1	198	383	49.14	0.01
Avg	**256.9**	**27.2**	**225.1**	**509.2**	**154.8**	**2.5**	**142.9**	**300.2**	**35.41**	**0.03**
TEST-2{10, 1, 5}										
1	1035	22	1480	2537	293	1	421	715	71.82	0.06
2	598	57	417	1072	291	2	202	495	53.82	0.06
3	958	71	686	1715	347	4	276	627	63.44	0.03
4	674	53	902	1629	246	1	244	491	69.86	0.04
5	1165	55	1567	2787	334	1	401	736	73.59	0.04
6	928	64	847	1839	258	1	257	516	71.94	0.09
7	1172	53	699	1924	381	1	244	626	67.46	0.11
8	738	49	1259	2046	325	1	468	794	61.19	0.07
9	708	38	390	1136	334	1	246	581	48.86	0.25
10	949	53	658	1660	300	1	206	507	69.46	0.15
TEST-3{10, 1, 10}										
1	892	60	895	1847	270	2	313	585	68.33	0.14
2	662	40	863	1565	275	1	297	573	63.39	0.06
3	838	35	798	1671	403	1	358	762	54.40	0.09
4	873	53	1091	2017	361	1	439	801	60.29	0.09
5	1267	60	1176	2503	468	1	379	848	66.12	0.05
6	716	52	514	1282	275	1	245	521	59.36	0.10
7	912	75	754	1741	362	3	282	647	62.84	0.14
8	953	36	754	1743	309	1	232	542	68.90	0.10
9	1096	54	1053	2203	251	2	300	553	74.90	0.17
10	425	36	963	1424	187	1	282	470	66.99	0.17
Avg	**892.5**	**51.5**	**890.5**	**1834.5**	**310.9**	**1.4**	**296.5**	**608.8**	**65.14**	**0.09**

Test-4{15, 1, 5}										
1	1450	66	1950	3466	353	1	412	766	77.90	0.10
2	2417	75	2395	4887	511	1	537	1049	78.53	0.07
3	2293	91	2217	4601	590	1	651	1242	73.01	0.17
4	1537	75	2174	3786	290	1	426	717	81.06	0.15
5	2516	83	2224	4823	589	1	452	1042	78.40	0.19
6	1548	85	1322	2955	399	1	330	730	75.30	0.27
7	1597	85	2121	3803	466	1	544	1011	73.42	0.13
8	1651	67	2393	4111	366	1	464	831	79.79	0.12
9	1786	81	2220	4087	424	1	564	989	75.80	0.09
10	2407	89	1311	3807	526	1	351	878	76.94	0.08
TEST-5{15,1,10}										
1	830	85	608	1523	272	1	242	515	66.19	0.04
2	1900	94	1680	3674	442	2	412	856	76.70	0.20
3	1874	94	2423	4391	445	1	584	1030	76.54	0.19
4	1949	72	2336	4357	383	1	501	885	79.69	0.18
5	2848	87	2328	5263	666	1	535	1202	77.16	0.22
6	2250	63	1919	4232	548	1	542	1091	74.22	0.08
7	2306	95	2310	4711	521	1	517	1039	77.95	0.04
8	2023	90	1891	4004	565	2	493	1060	73.53	0.04
9	1960	81	1108	3149	386	2	289	677	78.50	0.04
10	1865	96	1811	3772	402	1	417	820	78.26	0.05
Avg	**1920.2**	**79.7**	**2032.7**	**4032.6**	**451.4**	**1**	**473.1**	**925.5**	**77.01**	**0.14**
Test-6 {20, 1, 5}										
1	2840	102	3275	6217	488	1	557	1046	83.18	0.14
2	2785	99	1787	4671	642	1	410	1053	77.46	0.16
3	3122	112	1804	5038	594	1	312	907	82.00	0.23
4	3274	109	2716	6099	710	1	544	1255	79.42	0.07
5	3250	109	2769	6128	628	1	616	1245	79.68	0.10
6	3898	95	3119	7112	698	1	559	1258	82.31	0.08
7	4732	95	3511	8338	758	1	536	1295	84.47	0.18
8	3527	118	2858	6503	699	1	578	1278	80.35	0.07
9	4102	109	3501	7712	727	1	661	1389	81.99	0.09
10	3774	97	3279	7150	737	1	634	1372	80.81	0.09
TEST-7 {20, 1, 10}										
1	4347	105	4679	9131	797	1	856	1654	81.89	0.09
2	2498	97	3300	5895	414	1	617	1032	82.49	0.07
3	2663	101	3303	6067	441	2	559	1002	83.48	0.07
4	2296	123	2418	4837	512	1	587	1100	77.26	0.25
5	3509	118	3197	6824	605	1	561	1167	82.90	0.30
6	1866	135	2767	4768	328	2	526	856	82.05	0.16
7	2947	114	3477	6538	580	2	728	1310	79.96	0.17
8	3149	113	2906	6168	612	1	571	1184	80.80	0.12
9	2705	127	2777	5609	458	2	517	977	82.58	0.09
10	2413	123	2855	5391	480	1	529	1010	81.27	0.09

Avg	**3530.4**	**104.5**	**2861.9**	**6496.8**	**668.1**	**1**	**540.7**	**1209.8**	**81.17**	**0.12**
TEST-8 {25, 1, 5}										
1	4250	144	5386	9780	716	1	862	1579	83.85	0.08
2	4770	117	4849	9736	724	1	755	1480	84.80	0.09
3	4838	152	5404	10394	816	1	936	1753	83.13	0.08
4	6123	131	5380	11634	913	1	821	1735	85.09	0.07
5	5383	122	5452	10957	817	1	859	1677	84.69	0.07
6	4749	163	4674	9586	747	1	635	1383	85.57	0.08
7	3900	139	4835	8874	538	1	745	1284	85.53	0.07
8	5470	116	5530	11116	762	1	801	1564	85.93	0.07
9	6431	131	5844	12406	917	1	929	1847	85.11	0.07
10	5250	133	3454	8837	869	1	700	1570	82.23	0.08
TEST-9 {25, 1, 10}										
1	6924	153	5646	12723	975	1	777	1753	86.22	0.07
2	5527	128	6157	11812	792	1	866	1659	85.95	0.07
3	5810	125	6770	12705	830	1	1035	1866	85.31	0.07
4	5375	144	4842	10361	720	2	679	1401	86.48	0.08
5	4155	136	4773	9064	692	1	810	1503	83.42	0.07
6	4551	159	4654	9364	731	2	704	1437	84.65	0.08
7	4539	133	4000	8672	825	1	733	1559	82.02	0.07
8	5934	129	5366	11429	817	1	757	1575	86.22	0.07
9	5585	115	5679	11379	773	1	914	1688	85.17	0.07
10	3297	110	3156	6563	570	1	578	1149	82.49	0.07
Avg	**5116.4**	**134.8**	**5080.8**	**10332**	**781.9**	**1**	**804.3**	**1587.2**	**84.59**	**0.07**
TEST-10 {30, 1, 5}										
1	6017	164	5794	11975	733	1	712	1446	87.92	0.10
2	6319	159	7167	13645	858	1	978	1837	86.54	0.10
3	7491	171	7727	15389	783	1	861	1645	89.31	0.10
4	7963	152	8644	16759	1079	1	971	2051	87.76	0.10
5	7909	145	6882	14936	984	1	786	1771	88.14	0.10
6	7810	125	7011	14946	1117	1	889	2007	86.57	0.10
7	6430	194	5640	12264	1027	1	892	1920	84.34	0.11
8	7650	179	7600	15429	929	1	963	1893	87.73	0.10
9	9493	151	5556	15200	1152	1	714	1867	87.72	0.10
10	7691	214	7637	15542	908	1	829	1738	88.82	0.10
TEST-11 {30, 1, 10}										
1	6704	156	9946	16806	761	1	1092	1854	88.97	0.09
2	6717	167	7976	14860	890	1	929	1820	87.75	0.09
3	5902	159	4671	10732	939	1	729	1669	84.45	0.10
4	9363	185	8449	17997	1097	1	982	2080	88.44	0.10
5	8155	141	8235	16531	1121	1	965	2087	87.38	0.09
6	7536	159	7905	15600	925	1	877	1803	88.44	0.09
7	6777	142	8615	15534	925	1	1123	2049	86.81	0.09
8	6837	156	6241	13234	922	1	945	1868	85.88	0.11
9	7010	156	4387	11553	859	1	642	1502	87.00	0.09

10	6686	167	5412	12265	883	1	784	1668	86.40	0.21
Avg	**7477.3**	**165.4**	**6965.8**	**14608.5**	**957**	**1**	**859.5**	**1817.5**	**87.49**	**0.10**
TEST-12 {35, 1, 5}										
1	8481	202	7531	16214	1050	2	953	2005	87.63	0.13
2	7732	192	5922	13846	842	1	708	1551	88.80	0.13
3	12978	208	12015	25201	1247	1	1183	2431	90.35	0.13
4	9512	205	8594	18311	1016	1	920	1937	89.42	0.13
5	9553	180	8559	18292	1023	1	1019	2043	88.83	0.14
6	10521	188	9609	20318	1055	1	924	1980	90.25	0.14
7	7507	209	8768	16484	864	1	1063	1928	88.30	0.13
8	8387	238	8398	17023	927	1	904	1832	89.24	0.13
9	8316	159	8802	17277	949	1	923	1873	89.16	0.14
10	9991	209	8554	18754	1151	1	947	2099	88.81	0.13
TEST-13 {35, 1, 10}										
1	10273	214	11759	22246	1135	1	1193	2329	89.53	0.13
2	12749	209	10236	23194	1167	2	1003	2172	90.64	0.12
3	12155	190	10676	23021	1298	2	1113	2413	89.52	0.13
4	9469	207	10137	19813	971	1	1161	2133	89.23	0.13
5	7955	191	10235	18381	890	1	1147	2038	88.91	0.12
6	9403	206	6285	15894	1010	1	792	1803	88.66	0.12
7	7914	230	7981	16125	870	1	1044	1915	88.12	0.12
8	9655	216	8501	18372	1143	1	983	2127	88.42	0.12
9	6979	167	7936	15082	898	1	1139	2038	86.49	0.13
10	8860	214	8937	18011	989	1	961	1951	89.17	0.12
Avg	**9297.8**	**199**	**8675.2**	**18172**	**1012.4**	**1.1**	**954.4**	**1967.9**	**89.08**	**0.13**

Enhanced model experiment results

Instance	Initial U_{jk}	Initial h_{tk}	Initial S_j	Initial C_{jt}	Initial Total Cost	Optimized U_{jk}	Optimized h_{tk}	Optimized S_j	Optimized C_{jt}	Optimized Total Cost	%Improved	Computational Time (s)
Test-1 : {A=1, B=35, C=10, D=10}												
1	366	0	54	71	491	192	73	32	17	314	63.95	0.14
2	613	0	68	66	747	429	110	40	19	598	80.05	0.20
3	397	0	69	66	532	335	37	51	24	447	84.02	0.20
4	360	0	56	81	497	278	62	40	20	400	80.48	0.18
5	384	0	59	65	508	269	54	39	21	383	75.39	0.22
Test-2 : {A=1, B=35, C=10, D=20}												
1	537	0	66	79	682	408	73	45	23	549	80.50	0.23
2	459	0	54	67	580	390	43	42	21	496	85.52	0.19
3	640	0	66	77	783	501	84	46	20	651	83.14	0.26
4	581	0	61	68	710	388	112	46	21	567	79.86	0.19
5	499	0	68	79	646	379	107	40	20	546	84.52	0.30
Test-3 : {A=1, B=35, C=10, D=30}												
1	471	0	53	67	591	369	57	35	20	481	81.39	0.23
2	464	0	56	62	582	291	104	34	21	450	77.32	0.54
3	535	0	60	74	669	304	102	38	18	462	69.06	0.37
4	480	0	54	68	602	303	88	32	17	440	73.09	0.38
5	466	0	57	66	589	368	50	38	20	476	80.81	0.48
Test-4 : {A=1, B=35, C=10, D=40}												
1	415	0	62	59	536	251	121	40	21	433	80.78	0.71
2	453	0	65	65	583	299	77	48	21	445	76.33	0.51
3	559	0	50	68	677	409	106	31	18	564	83.31	0.63
4	501	0	61	68	630	387	78	42	22	529	83.97	0.34
5	494	0	66	71	631	354	96	38	18	506	80.19	0.53
Test-5: {A=1, B=35, C=10, D=50}												
1	421	0	61	75	557	283	81	34	17	415	74.51	0.66
2	423	0	59	72	554	302	71	42	19	434	78.34	0.53
3	564	0	64	65	693	336	139	37	20	532	76.77	0.51
4	592	0	63	67	722	408	145	41	20	614	85.04	0.53
5	429	0	50	66	545	285	79	33	17	414	75.96	0.34
Test-6: {A=10, B=35, C=10, D=10}												
1	5428	0	78	67	5573	3876	935	78	47	4936	88.57	0.66
2	4708	0	70	76	4854	3273	766	70	39	4148	85.46	0.52
3	4739	0	69	69	4877	3424	739	69	37	4269	87.53	0.49
4	4680	0	69	78	4827	3420	694	69	36	4219	87.40	0.51
5	4940	0	70	66	5076	3501	761	70	46	4378	86.25	1.47

Test-7 : {A=10, B=35, C=10, D=20}												
1	4782	0	72	69	4923	3279	763	72	37	4151	84.32	1.68
2	4799	0	71	68	4938	3494	689	71	40	4294	86.96	1.53
3	4571	0	70	79	4720	3366	613	70	41	4090	86.65	1.37
4	4779	0	67	71	4917	3139	878	67	39	4123	83.85	1.66
5	5042	0	61	85	5188	3515	846	61	35	4457	85.91	1.16
Test-8 : {A=10, B=35, C=10, D=30}												
1	4842	0	64	71	4977	3550	765	64	36	4415	88.71	1.44
2	4804	0	70	68	4942	3431	736	70	36	4273	86.46	1.95
3	4799	0	63	67	4929	3532	640	63	42	4277	86.77	1.50
4	4716	0	60	67	4843	3366	735	60	38	4199	86.70	1.35
5	4872	0	77	65	5014	3526	723	74	34	4357	86.90	1.44
Test-9 : {A=10, B=35, C=10, D=40}												
1	4912	0	75	72	5059	3587	726	75	42	4430	87.57	1.64
2	4999	0	74	74	5147	3637	808	74	36	4555	88.50	1.53
3	4726	0	68	69	4863	3348	691	68	49	4156	85.46	2.37
4	5343	0	81	74	5498	3980	742	81	39	4842	88.07	2.01
5	4885	0	66	71	5022	3571	716	66	36	4389	87.40	1.41
Test-10 : {A=10, B=35, C=10, D=50}												
1	5010	0	70	65	5145	3490	864	70	42	4466	86.80	1.69
2	4445	0	67	74	4586	3144	739	67	41	3991	87.03	1.78
3	5164	0	76	72	5312	3705	743	76	36	4560	85.84	1.78
4	5023	0	69	70	5162	3573	802	69	48	4492	87.02	2.27
5	4554	0	62	77	4693	3197	793	62	40	4092	87.19	1.42
Test-11 : {A=15, B=35, C=10, D=10}												
1	7013	0	68	74	7155	5187	1029	68	48	6332	88.50	0.82
2	6851	0	78	69	6998	5059	950	78	53	6140	87.74	0.85
3	7423	0	72	70	7565	5354	1184	72	60	6670	88.17	0.91
4	7396	0	72	67	7535	5137	1344	72	53	6606	87.67	0.87
5	6952	0	68	60	7080	4822	1102	68	64	6056	85.54	1.19
Test-12 : {A=15, B=35, C=10, D=20}												
1	7319	0	73	84	7476	5307	1174	73	69	6623	88.59	1.11
2	7989	0	74	66	8129	6115	1001	74	55	7245	89.13	1.20
3	7237	0	68	70	7375	5143	1222	68	53	6486	87.95	2.14
4	7048	0	72	72	7192	5154	1022	72	51	6299	87.58	2.07
5	7663	0	65	75	7803	5736	1032	65	64	6897	88.39	0.99
Test-13 : {A=15, B=35, C=10, D=30}												
1	6874	0	59	63	6996	4980	977	59	53	6069	86.75	3.16
2	6323	0	63	69	6455	4323	1030	63	46	5462	84.62	1.88
3	7291	0	66	77	7434	5363	1080	66	52	6561	88.26	2.65
4	7351	0	68	77	7496	5096	1301	68	49	6514	86.90	2.64

5	7064	0	68	63	7195	5046	1156	68	58	6328	87.95	2.96
Test-14 : {A=15, B=35, C=10, D=40}												
1	7261	0	73	73	7407	4895	1361	73	49	6378	86.11	2.29
2	6975	0	64	76	7115	5085	1062	64	54	6265	88.05	2.94
3	6927	0	71	74	7072	4993	1025	71	56	6145	86.89	3.73
4	6938	0	74	65	7077	5286	962	74	56	6378	90.12	2.52
5	6962	0	76	74	7112	4928	1047	76	55	6106	85.85	2.40
Test-15 : {A=15, B=35, C=10, D=50}												
1	6984	0	76	69	7129	5195	944	76	48	6263	87.85	2.92
2	7141	0	71	70	7282	4969	1157	71	47	6244	85.75	2.67
3	7004	0	78	68	7150	4992	1180	78	56	6306	88.20	2.88
4	7475	0	66	60	7601	5521	1090	66	53	6730	88.54	2.40
5	7726	0	66	73	7865	5358	1279	66	65	6768	86.05	3.53
Test-16 : {A=25, B=35, C=10, D=10}												
1	11631	0	80	73	11784	8476	1741	80	97	10394	88.20	1.59
2	12102	0	64	80	12246	8517	1969	64	90	10640	86.89	1.58
3	11967	0	66	73	12106	8545	1911	66	78	10600	87.56	1.59
4	12223	0	64	72	12359	9155	1653	64	73	10945	88.56	2.09
5	12304	0	66	79	12449	8773	1895	66	93	10827	86.97	1.74
Test-17 : {A=25, B=35, C=10, D=20}												
1	11895	0	77	68	12040	8608	1855	77	78	10618	88.19	1.61
2	12006	0	71	68	12145	8584	1913	71	77	10645	87.65	1.55
3	12335	0	68	70	12473	8462	2143	68	84	10757	86.24	1.60
4	11449	0	70	62	11581	8769	1500	70	73	10412	89.91	1.80
5	12514	0	75	68	12657	8848	2027	75	81	11031	87.15	1.65
Test-18 : {A=25, B=35, C=10, D=30}												
1	11719	0	74	74	11867	8025	1944	74	76	10119	85.27	1.55
2	12428	0	68	61	12557	9214	1798	68	84	11164	88.91	1.66
3	12083	0	62	74	12219	8835	1852	62	79	10828	88.62	2.28
4	12845	0	64	73	12982	9412	1902	64	73	11451	88.21	1.66
5	12026	0	70	73	12169	8339	2051	70	79	10539	86.61	1.75
Test-19 : {A=25, B=35, C=10, D=40}												
1	11802	0	66	67	11935	8289	1866	66	81	10302	86.32	1.79
2	11822	0	76	63	11961	8679	1806	76	69	10630	88.87	5.10
3	12036	0	67	75	12178	8848	1707	67	70	10692	87.80	4.51
4	12257	0	66	73	12396	8514	2074	66	81	10735	86.60	5.21
5	12230	0	74	69	12373	8619	1951	74	70	10714	86.59	1.68
Test-20 : {A=25, B=35, C=10, D=50}												
1	12007	0	71	77	12155	8597	1970	71	80	10718	88.18	8.66
2	11610	0	71	74	11755	8091	1898	71	78	10138	86.24	5.19
3	11883	0	77	82	12042	8437	1731	77	68	10313	85.64	5.41

4	11860	0	74	72	12006	8108	2080	74	90	10352	86.22	5.12
5	11759	0	61	72	11892	7906	2237	61	71	10275	86.40	5.48

Supplier integrated model experiment results

Instance	Initial u_{jks}	Initial b_j	Initial h_{ik}	Initial l_i	Initial_ c_{jrs}	Initial_ p_j	Initial Total cost	Opt._ u_{jks}	Opt. b_j	Opt. h_{jk}	Opt. l_j	Opt. c_{jrs}	Opt. p_j	Opt. Total Cost	%Improvement	Computational Time
A=1 ,B=1,C=35,D=10,E=25																
1	359	100	0	0	302	9831	10592	33	6	100	218	4	85	446	95.79	106.7
2	482	94	0	0	298	9566	10440	8	6	86	245	7	33	385	96.31	2.90
3	392	107	0	0	318	10366	11183	21	7	256	197	2	58	541	95.16	0.16
A=1 ,B=5,C=35,D=10,E=25																
1	2430	111	0	0	308	7127	9976	233	40	484	838	25	56	1676	83.20	600.2
2	2391	106	0	0	312	8477	11286	174	15	412	982	11	14	1608	85.75	62.05
3	2276	108	0	0	303	5960	8647	367	46	329	794	43	59	1638	81.06	600.2
A=1 ,B=10,C=35,D=10,E=25																
1	5237	98	0	0	315	1600	7250	1087	67	771	1736	72	86	3819	47.32	600.3
2	4854	117	0	0	319	3379	8669	906	61	724	1606	56	78	3431	60.42	600.4
3	4885	100	0	0	324	2665	7974	876	65	773	1726	58	70	3568	55.25	600.2
A=1 ,B=15,C=35,D=10,E=25																
1	6833	112	0	0	343	-367	6921	1188	92	1104	1939	102	65	4490	35.12	600.4
2	7066	105	0	0	311	-754	6728	1603	87	895	1957	75	64	4681	30.43	600.3
3	7200	120	0	0	307	1059	8686	1214	83	1052	2414	65	14	4842	44.26	600.4
A=1 ,B=25,C=35,D=10,E=25																
1	12235	102	0	0	329	-4114	8552	2673	95	1560	3825	114	7	8274	3.25	279.1
A=2 ,B=1,C=35,D=10,E=25																
1	930	210	0	0	624	19680	21444	29	15	86	264	9	40	443	97.93	600.2
2	961	200	0	0	629	20140	21930	32	3	146	186	3	106	476	97.83	0.51
3	911	188	0	0	636	15304	17039	7	8	144	190	10	60	419	97.54	600.3
A=2 ,B=5,C=35,D=10,E=25																
1	5201	238	0	0	620	13322	19381	346	48	440	898	24	39	1795	90.74	600.4
2	4780	220	0	0	599	15480	21079	140	42	495	887	17	79	1660	92.12	600.3
3	5079	194	0	0	646	15146	21065	242	37	473	1001	16	81	1850	91.22	600.3
A=2 ,B=10,C=35,D=10,E=25																
1	9430	232	0	0	616	3644	13922	1137	89	675	966	59	91	3017	78.33	600.6
2	10072	210	0	0	595	3864	14741	1166	89	657	1273	45	83	3313	77.53	600.6
3	9572	194	0	0	604	2548	12918	1003	89	634	1252	64	53	3095	76.04	600.4
A=2 ,B=15,C=35,D=10,E=25																
1	14793	226	0	0	601	-6382	9238	1832	143	811	1661	81	135	4663	49.52	601.1

2	14824	224	0	0	568	-3188	12428	2024	128	754	1736	72	71	4785	61.50	600.7
3	13928	214	0	0	672	-2412	12402	1779	117	771	1653	76	11	4407	64.47	600.9
A=2 ,B=25,C=35,D=10,E=25																
1	25056	162	0	0	622	-12904	12936	3424	126	1023	2382	113	52	7120	44.96	600.9
2	23806	204	0	0	598	-16532	8076	3319	175	1070	2095	117	46	6822	15.53	601.3
3	25659	222	0	0	642	-18446	8077	3512	193	1132	2642	128	139	7746	4.10	601.3
A=3 ,B=1,C=35,D=10,E=25																
1	1290	306	0	0	941	26505	29042	25	15	100	226	6	95	467	98.39	600.2
2	1290	270	0	0	953	27180	29693	32	10	68	210	7	68	395	98.67	600.2
3	1127	327	0	0	948	30345	32747	18	8	65	218	6	45	360	98.90	600.3
A=3 ,B=5,C=35,D=10,E=25																
1	7532	354	0	0	944	21531	30361	239	27	386	1029	24	58	1763	94.19	600.6
2	7243	318	0	0	937	15792	24290	369	45	384	718	31	20	1567	93.55	600.8
3	7163	273	0	0	906	22626	30968	281	29	360	857	24	99	1650	94.67	600.5
A=3 ,B=10,C=35,D=10,E=25																
1	14145	327	0	0	926	3915	19313	1008	107	532	1357	64	63	3131	83.79	600.8
2	14323	333	0	0	966	13899	29521	909	75	716	1323	48	66	3137	89.37	600.7
3	14416	327	0	0	978	7404	23125	777	83	604	1383	53	27	2927	87.34	600.8
A=3 ,B=15,C=35,D=10,E=25																
1	22374	360	0	0	926	-7020	16640	1544	139	843	1664	82	123	4395	73.59	601.3
2	21296	339	0	0	894	-5211	17318	1477	136	768	1699	70	33	4183	75.85	601.0
3	21355	285	0	0	918	-2181	20377	1670	110	642	1814	84	33	4353	78.64	601.0
A=3 ,B=25,C=35,D=10,E=25																
1	35622	291	0	0	972	-20598	16287	2632	187	1171	1932	110	167	6199	61.94	601.5
2	38152	318	0	0	953	-29676	9747	3417	207	1006	2249	130	91	7100	27.16	601.6
3	36886	306	0	0	949	-23832	14309	3255	183	1046	1714	115	35	6348	55.64	601.5

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