Hub Location Optimization in Reverse Supply Chain of Deconstructed Steel Building Components

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Abstract

Hub Location Optimization in a Proposed Reverse Supply Chain Model Deconstructed Steel Building Components

Hosna Ghorab, M.A.Sc

The construction industry has traditionally adhered to a linear economic model, commonly known as "take, make, dispose." In light of the escalating environmental challenges, the construction industry is undergoing a transformative shift towards a Circular Economy (CE) approach, emphasizing the reconsideration of material and component usage in construction with a primary focus on maximizing their lifespan and potential for reuse as components resulting from disassembling or deconstructing the building. At the component reuse level, deconstruction becomes pivotal.

Prefabricated construction represents a significant advancement in the realm of deconstruction, elevating disassembly practices to a more prominent position. The meticulous disassembly of components during this process facilitates their potential for reuse. However, despite these promising developments, a critical challenge facing adaption of CE is the underdeveloped market for supply and demand for these components.

One strategic approach to influence the market efficiently is the development of a Reverse Supply Chain (RSC) model, an area that remains largely neglected in current research.

This study aims to optimize the RSC for deconstructed steel building components. The main objectives are: (1) optimizing the RSC by finding the optimal locations of the reuse hubs based on minimizing the transportation costs and CO_2 emission, and (2) optimizing the operational efficiency of reuse hubs by developing a strategic roadmap that delineates optimal management practices to ensure timely market.

The optimal location of hubs within the RSC aims to efficiently connect critical nodes (i.e. deconstruction sites, hubs, recycle centers, factories, and end-users) by integrating a Genetic Algorithm (GA) and a Geographic Information System (GIS). The study also examines supply-demand ratios and facility capacities to create a more practical model for future real-world applications. Simulation results based on estimated geographic building locations and the potential hub locations demonstrate the effectiveness of the proposed method in identifying optimal hub placements while minimizing CO_2 emission in transportation. Then, to achieve greater efficiency in this model, it is essential to evaluate the functionality of hubs after their placement in optimal locations within the model. Key functions include conducting quality inspections based on component stages, facilitating refurbishment processes, and managing the marketing and storage of components to extend their lifecycle.

This research provides valuable insights for firms seeking to implement sustainable, profit-driven strategies and contribute to the advancement of CE practices in the construction industry.

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List of Abbreviations

Abbreviation	Full Term
BAMB	Building as Material Banks
BIM	Building Information Modeling
CDW	Construction and Demolition Waste
CE	Circular Economy
CTD	Cut and Take Down
DMFA	Dynamic Material Flow Analysis
DfCE	Design for Circular Economy
DfD/A	Design for Disassembly/Adaptation
DfM/A	Design for Manufacturing/Assembly
DfRL	Design for Reverse Logistic
DPP	Digital Product Passport
EA	Evolutionary Algorithm
EOL	End-of-Life
EPD	Environmental Product Declaration
FCS	Forward Supply Chain
GA	Genetic Algorithm
GIS	Geographic Information System
IOT	Internet of Things
JIT	Just in Time
LCA	Life-Cycle Assessment
LP	Linear Programming
MFA	Material Flow Analysis
MP	Material Passport
MILP	Mixed-Integer Linear Programming
NFE	Number of Function Evaluations
OSM	OpenStreetMap
PSO	Particle Swarm Optimization
QA	Quality Assurance

RSC	Reverse Supply Chain
SA	Simulated Annealing
SCM	Supply Chain Management

Chapter 1. Introduction

1.1 Background

The resource depletion and climate change have caused societies worldwide to face extraordinary challenges. Consequently, there is an increasing global demand for a profound shift in the way individuals and businesses engage with the environment, urging transformative change. The construction industry, on a global scale, is widely recognized for its substantial consumption of raw materials, water, and energy, as well as its significant contribution to greenhouse gas emissions and carbon dioxide (CO_2) released into the atmosphere (Ginga et al., 2020). It accounts for approximately 40% of total energy consumption, generates around 30% of greenhouse gas emissions, utilizes about 17% of freshwater resources, and contributes to deforestation by consuming 25% of harvested wood worldwide (Badi & Murtagh, 2019; Chileshe et al., 2018; Eberhardt et al., 2022). Annually, substantial amounts of waste are produced at the building End-of-Life (EOL), to be eventually recycled, reused, or, in many cases, disposed at waste management facilities.

To mitigate the environmental impact of Construction and Demolition Waste (CDW), the adoption of Circular Economy (CE) principles has emerged as a viable and necessary solution (Ostapska et al., 2024) because only a small portion of CDW is allowed to go to landfill. The majority of materials are being used as down-cycling sources (Zhang et al., 2020). By using Life Cycle Assessment (LCA), CE is trying to change the destiny of CDW from landfill to recycling (Di Maria et al., 2018).

Unlike traditional linear models, which treat materials as single use resources, a CE model prioritizes longevity, reuse, and adaptability in materials and components (Mahpour, 2018). This is facilitated through Design for Disassembly/Adaptation (DfD/A), recycling, and repurposing (Ostapska et al., 2024; Rios et al., 2015). A fundamental aspect of this approach is shifting from demolition to deconstruction, allowing for the recovery and reintegration of building materials and components into new construction projects.

At the core of this transition is the Reverse Supply Chain (RSC), which plays a crucial role in managing the flow of deconstructed materials. Unlike the Forward Supply Chain (FSC), which focuses on the procurement and delivery of new materials (Benachio et al., 2020), the RSC facilitates the collection, refurbishment, and redistribution of reclaimed components (Ding et al., 2023). Despite its potential, the RSC remains largely underdeveloped, with limited practical implementation models that integrate modular construction with deconstruction practices. A well-structured RSC is essential for managing the entire lifecycle of construction components (Rios et al., 2015), ensuring that materials are efficiently reclaimed, refurbished, and reintroduced into the construction process, thereby reducing waste and minimizing environmental impact.

At the material level, a circular approach emphasizes the use of sustainable and recyclable materials throughout the construction lifecycle. This involves identifying alternative materials with lower environmental footprints and implementing tracking systems such as building Material Passports (MPs) to monitor and manage material flows (Benachio et al., 2020).

At the component level, designing and manufacturing building elements for reusability and adaptability is crucial. Modular construction techniques enable the easy assembly, disassembly, and reuse of standardized components, ensuring longevity and flexibility in building designs (Rios et al., 2015). The implementation of a Digital Product Passport (DPP) further enhances these efforts by providing comprehensive data on material composition, sustainability metrics, and potential reuse or recycling strategies (Adisorn et al., 2021).

Off-site construction methodologies offer significant environmental benefits by reducing on-site waste generation, lowering transportation-related emissions, and improving overall construction efficiency. In particular, prefabricated and modular construction systems, together with the use of reversible connections, play a pivotal role in facilitating transition to circular construction. These approaches support the concept of "building for longevity" by enabling structures to be adaptable to both present and future functional requirements (Allam & Nik-Bakht, 2023) and constitute a key strategy within DfD.

1.2 Problem Statement

Despite the increasing emphasis on CE principles in the construction industry, the effective reuse of deconstructed building components remains limited. While deconstruction, modular construction, and DfD aim to retain component value beyond the End-of-Life (EOL) stage, current industry practices lack the systemic and operational mechanisms required to support a viable second lifecycle for building components. This limitation can be attributed to two fundamental and interrelated problems.

The first major problem is the lack of a comprehensive, integrated, and data-driven RSC capable of managing deconstructed components beyond their removal from EOL buildings. Existing RSC models in the construction sector are highly fragmented and predominantly oriented toward waste handling rather than value retention. In particular, there is an absence of integrated systems that effectively link deconstruction sites, refurbishment and repair activities, storage facilities, manufacturing centers, recycling facilities, and potential end-users within a unified and optimized network. This fragmentation is further exacerbated by the lack of reliable data infrastructures to track building components, including their technical specifications, condition, reuse potential, and compatibility with future projects.

Although concepts such as MPs and DPPs have been proposed to facilitate information transparency and traceability, their integration into reverse supply chain decision-making remains limited. As a result, critical information required to match recovered components with suitable end users is often unavailable or disconnected from logistical and operational planning. This disconnect significantly reduces the feasibility of component reuse, increases uncertainty, and discourages industry adoption of circular construction practices, ultimately leading to the downcycling or recycling of components that could otherwise be reused.

The second major problem is the absence of a dedicated physical and operational node within the RSC that can effectively connect and coordinate the various stakeholders and processes involved in circular construction. Current reverse logistics configurations often rely on direct or loosely coordinated flows between deconstruction sites, recycling centers, factories, and end-users, resulting in inefficient transportation, increased costs, and limited scalability. The lack of strategically defined intermediary facilities, hubs, represents a critical gap in the RSC.

These hubs are envisioned as centralized locations where deconstructed components can be inspected, sorted, repaired, refurbished, upgraded, and temporarily stored before redistribution. In addition, hubs can serve as coordination points for outsourcing refurbishment processes to specialized factories and for managing supply–demand matching based on component condition, availability, and end-user requirements. Without such hubs, the RSC lacks the structural capacity to consolidate material flows, optimize transportation routes, and synchronize refurbishment and reuse activities, thereby undermining the economic and environmental viability of component reuse at scale.

1.3 Objectives

To address these challenges, it is essential to develop a practical RSC that enhances the efficiency of deconstruction and facilitates the reintegration of reclaimed components into new construction projects. A well-designed RSC enables optimizing resource allocation identifying the locations of supply and demand hubs, and improving the estimation of transportation costs. It ensures that materials and components are not only recovered but also effectively reintegrated into the construction ecosystem, minimizing environmental impact and supporting the transition to CE.

The primary objective of this study is to develop and optimize a hub-based RSC model for deconstructed building components that supports CE principles. This involves establishing an integrated RSC framework in which hubs function as central coordination nodes connecting deconstruction sites, refurbishment and repair facilities, recycling centers, and end-users. The framework is optimized by determining the optimal spatial locations of hubs to minimize total transportation costs and associated environmental impacts, including CO_2 emissions.

In addition, this research aims to define and plan optimal hub functions within the RSC. In this context, hubs are envisioned as centralized facilities where deconstructed components undergo quality inspection, sorting, repair, refurbishment, upgrading, and temporary storage. These functions enable the preparation of recovered components for second-life applications and support effective matching between component availability and end-user demand based on component condition, characteristics, and reuse potential.

1.4 Thesis Organization

The structure of this thesis is presented as follows:

Chapter 2. Literature Review: presents a systematic review of relevant academic studies and technical documents related to the application of CE principles in the construction industry. This chapter examines existing practices for managing building materials and components after demolition, with particular emphasis on recycling, reuse, and deconstruction strategies. It provides an overview of current circular construction practices and highlights emerging research trends aimed at reducing environmental impacts throughout the building lifecycle. These include design- and construction-stage strategies, as well as deconstruction and disassembly approaches at the EOL stage, to enable component reuse and second-life applications. In addition, this chapter reviews existing frameworks for material and component reuse and discusses optimization approaches, including technological advancements and theoretical models, developed to improve their performance.

Chapter 3. Methodology: describes the research methodology adopted to achieve the study objectives. This chapter outlines the development and optimization of a hub-based RSC framework, including the formulation of the allocation problem and the optimization approach. The chapter details the use of a geographic and spatial computer-based framework to model the RSC and determine optimal hub locations and component flows.

Chapter 4. Conceptual framework for RSC for Component Reuse: introduces the proposed RSC framework and defines the role of hubs within the system. This chapter is more focused on the operational functions of the hubs, including inspection, repair, refurbishment, storage, and redistribution processes, and describes how deconstructed components are prepared and reintroduced into the market through the hub network.

Chapter 5. Implementation and Case Study: presents the application of the proposed RSC framework using real-world data. A case study is conducted to evaluate the practicality, reliability, and performance of the proposed network, demonstrating its effectiveness in facilitating the reuse of deconstructed building components and optimizing the RSC configuration.

Chapter 6. Conclusions and Future Work: summarizes the research findings and highlights the key contributions of the study. This chapter also discusses the limitations of the research and identifies potential directions for future work.

Chapter 2. Literature Review

2.1 Introduction

In this chapter, a systematic review of previous research on CE principles adoption in construction industry is conducted. This review examines existing practices for managing building materials and components after demolition, with particular emphasis on recycling, reuse, and deconstruction strategies. Then the methods to optimize these practices are being discussed, including technological advancements and theoretical models.

2.2 CE in Construction Industry

The significant environmental impacts, resource consumption, and waste generation stemming from buildings are sources of profound concern. As shown in Figure 2-1, the generation of waste during the entire lifecycle of buildings, including the planning and design phases, highlights a significant oversight in waste management (Esa et al., 2017). Implementing CE strategies in construction involves several key measures. Generally, the emphasis is placed on designing buildings and infrastructure with durability, adaptability, and disassembly in mind. This enables components and materials to be easily separated and reused at the end of their lifecycle, rather than being discarded as waste (Mahpour, 2018). Instead of treating buildings as structures with a limited life expectancy, the industry is increasingly embracing the concept of "building for longevity". This means designing buildings with the intent of extending their lifecycle and making them adaptable for future needs (Juan & Cheng, 2018).

The longevity of a building is closely associated with resilience, durability, and adaptability (Askar et al., 2021). While resilience and durability are sometimes used interchangeably, they have distinct meanings. Durability refers to a building's ability to withstand stress and maintain structural integrity over time (Schmidt III et al., 2010). In contrast, resilience encompasses not only endurance but also adaptability, the ability to respond to and recover from challenging conditions (Re Cecconi et al., 2018).

Resilience plays a crucial role in extending a building's service life and overall longevity, thereby contributing to sustainability in the construction industry (Askar et al., 2021). With advancements in technology, achieving sustainable built environments has become more feasible. One widely adopted strategy is off-site and modular construction (Benjamin et al., 2022). By manufacturing modular components in controlled environments (Li et al., 2020) rather than on-site, it is possible to apply higher quality processes, employ skilled labor more effectively, and facilitate easier maintenance later (Generalova et al., 2016). This approach enhances a building's lifecycle and simplifies the processes of disassembly and deconstruction, significantly reducing waste generation.

Manufacturers are increasingly producing essential building components in controlled environments. For example, precast concrete can be tailored to specific dimensions and mix compositions to align with project needs. This approach improves the concrete's strength by allowing it to cure fully, ensuring optimal durability before being delivered to the construction site (Tomek, 2017).

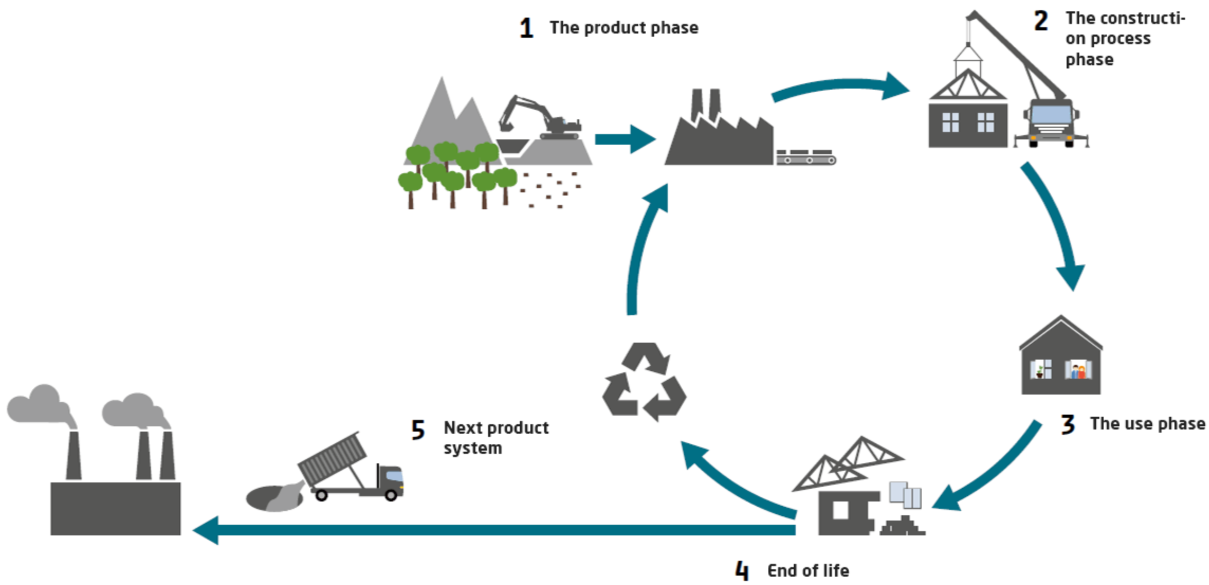


Figure 2-1 CE at the material level in the construction industry (Adapted from (Adeeba, 2023))

2.3 Material Recycling and Reuse

Over the years, various waste management techniques and strategies have been implemented, with the efficiency of waste handling becoming a key indicator of successful construction operations. Governments worldwide have introduced diverse policies aimed at reducing landfill waste, positioning waste minimization as a primary driver of construction waste management in numerous regions. For example, to ensure that the economic expansion linked to increased construction activities does not lead to excessive waste generation and environmental degradation, the European Union's Environment Action Plan (Directorate-General, 2010) prioritizes waste management throughout the entire project lifecycle. The management of CDW encompasses strategies for waste reduction, material reuse, and recycling during construction, renovation, and demolition activities, with the overarching goal of minimizing landfill disposal and mitigating environmental impacts (Ajayi et al., 2015).

Among the most widely implemented techniques are selective demolition, material-level recycling, and the recovery of components for direct reuse. Effective application of these techniques demands accurate quantification of environmental trade-offs, a task traditionally supported by LCA (Ajayi et al., 2015). LCA translates material inventories into environmental impact indicators (Ng & Chau, 2015), but it requires a robust physical accounting of where, when, and in what quantities materials move, a role fulfilled by Material Flow Analysis (MFA).

One emerging approach for operationalizing circularity at the building scale is the Building as Material Banks (BAMB) concept. BAMB employs MPs, documents that record the exact type, quantity, and location of materials in a building, to facilitate selective disassembly and maximize reuse potential at a building's EOL (Benachio et al., 2020). When combined with MFA, MPs provide the high-resolution data necessary for precise flow modelling, effectively linking micro-level tracking to macro-level CE metrics.

2.3.1 Material Flow Analysis (MFA)

MFA is a structured, quantitative method for tracking the movement and accumulation of specific materials, components, or substances within a clearly defined system over a particular time period and spatial boundary (Wu, 2024). Rooted in the principle of mass balance, where inputs equal outputs plus accumulation and adjusted for any losses (the materials which is sent to recycle centers or landfills for instance), MFA was originally developed within the field of industrial ecology to investigate the material metabolism of industrial systems and societies (Graedel & Allenby, 2010).

A state-of-the-art MFA typically unfolds through four iterative and interconnected stages (Korhonen, 2004). The process begins with system definition, which involves establishing a clear temporal horizon, geographic boundary, and functional unit to ensure consistency and relevance. This is followed by process mapping, where the various stages of the material lifecycle, such as production, use, maintenance, and EOL, are identified along with the corresponding material flows that link these stages. In the next step, data compilation is conducted using a range of sources including national statistics, bills of materials, site audits, and LCA databases (Graedel & Allenby, 2010). The collected data are subjected to mass balance checks to reconcile discrepancies and close data gaps, thereby ensuring the internal consistency of the system. Finally, synthesis and visualization techniques, such as Sankey diagrams or equivalent flow dashboards, are employed to communicate the results, highlighting critical areas like material leakage, in-use stocks, and potential points of inefficiency or intervention.

Static MFAs provide a one-year snapshot, whereas dynamic MFAs (dMFAs) link inflows to lifetime distributions so that future outflows from demolition or product retirement can be forecasted. Recent dMFA models of urban building stocks demonstrate how today's construction inflows become tomorrow's reusable supply (Hertwich et al., 2019).

MFA and LCA are complementary analytical tools that, when used in combination, provide a more comprehensive evaluation of CE strategies. MFA focuses on quantifying the movement and distribution of materials within a defined system, addressing the question of 'how much materials flows where.' In contrast, LCA assesses the environmental impacts associated with these material flows throughout their lifecycles. Integrating MFA's physically consistent inventories with the standardized framework of LCA, as outlined by ISO guidelines, enhances the robustness and reliability of sustainability assessments beyond what either method can achieve independently (ISO, 2006).

Since system boundaries can be extended or narrowed, MFA can trace materials from resource extraction through manufacturing, construction, use, maintenance, and ultimately EOL handling.

During design and construction, MFA based material budgets help project teams meet embodied-carbon targets and anticipate future waste streams. In the in-use phase, stock modelling quantifies the material reservoir locked in the built environment, informing urban-mining strategies. At the EOL stage, scenario-based MFAs compare selective demolition, mixed demolition, on-site sorting, and advanced recycling routes, highlighting trade-offs among cost, emissions, and reuse rates (Bringezu & Moriguchi, 2018).

At the reuse stage, MFA functions as a prospecting tool for urban mining. By quantifying the timing, location, and composition of demolition outflows, MFA reveals whether forthcoming secondary supply can meet future construction demand, guides reverse-logistics planning, and informs policy on quality standards for reclaimed components. Empirical studies in the Netherlands show that matching demolition and construction flows through dMFA can offset up to 40–50 % of primary material demand under favorable market and regulatory conditions (Leising et al., 2018).

The integration of MFA with Building Information Modeling (BIM), Geographic Information System (GIS), and Internet of Things (IoT) sensors is bridging the gap between static accounting and dynamic, real-time material tracking. Such digital enhancements deliver building-level data of sufficient granularity to update MFA inventories continuously, thereby strengthening decision-support for DfD, deconstruction logistics, and marketplace matching of reclaimed materials (Huang et al., 2020).

2.4 Component Reuse

Sustainability has become one of the most pressing and widely discussed concepts in contemporary society, reflecting growing global concerns regarding environmental degradation, resource scarcity, and the long term viability of human activities (Devaki & Shanmugapriya, 2022). Enabling building components to be carefully deconstructed, recovered, and reintegrated into new construction projects extends their lifecycle and significantly reduces the demand for raw materials. This practice aligns directly with the core principles of the CE, which prioritize resource conservation, waste minimization, and the continuous cycling of materials within the economy. Component reuse not only diverts waste from landfills but also reduces the embodied energy and carbon associated with producing new materials, thereby contributing to both environmental and economic sustainability (Tomek, 2017).

The integration of digital technologies plays a pivotal role in advancing CE principles within the construction industry. BIM is a key enabler, providing a digital framework that stores and manages data throughout a building's lifecycle from design and construction to operation and maintenance (Liu et al., 2015; Pan & Zhang, 2023). However, while BIM primarily supports a single lifecycle stage, MPs and DPP extend beyond this scope, enabling continuous tracking and reuse of components across multiple lifecycle stages. The DPP serves as a comprehensive digital repository that consolidates essential product data throughout its entire lifecycle (Adisorn et al., 2021). It facilitates the seamless exchange of technical, environmental, and circularity related information, fostering industry wide adoption of circularity and carbon neutral practices (Koppelaar et al., 2023). One of the DPP's core functionalities is the ability to trace a product's historical trajectory, monitor its movement across locations, and assess its suitability for reuse (Zhang & Seuring, 2024).

The architecture of a DPP system is built on a cross-sectoral IT infrastructure, enabling the development of future oriented digital tracking mechanisms (Jansen et al., 2023). Variations of DPPs can be classified into static and dynamic models. Static DPPs allow stakeholders to access product information without modification, while dynamic DPPs enable real time data updates, allowing stakeholders at different lifecycle stages to contribute new information. This evolution in digitalization fosters a centralized and harmonized exchange of data, essential for achieving an effective CE.

By integrating digital tracking systems such as DPPs within the RSC, the construction industry can optimize resource recovery, facilitate efficient component reuse, and significantly reduce waste generation (Çetin et al., 2023; Honic et al., 2021). The ability to accurately document material properties, durability, and maintenance history enhances decision-making processes, ensuring that reclaimed components meet quality standards before reintegration into new construction projects. As the construction industry shifts toward a circular model, leveraging digital tools like BIM and DPPs will be instrumental in fostering sustainable and resource efficient practices.

2.5 Life-Cycle Assessment (LCA) in Construction

LCA has become a central analytical framework for evaluating environmental performance in the construction sector. Defined by the ISO 14040 (Arvanitoyannis, 2008) and ISO 14044 standards, LCA quantifies environmental impacts across the entire lifecycle of a product or system, covering stages from raw material extraction and manufacturing to construction, use, maintenance, and EOL processing. In the built environment, this methodology enables a holistic understanding of both embodied and operational impacts, supporting evidence based decisions related to material selection, resource efficiency, and low carbon design strategies (Klöpffer, 2012). Numerous studies have demonstrated that environmental burdens in construction arise from multiple interconnected phases, and that a lifecycle perspective is necessary to prevent burden shifting and ensure performance improvements.

The importance of LCA has grown in parallel with the construction industry's contribution to global climate change. The building and construction sector is responsible for approximately 36 to 40% of global CO_2 emissions when operational and embodied impacts are combined. Embodied emissions alone; stemming from material extraction, manufacturing, transportation, and construction processes; account for roughly 11% of global energy related emissions (Waldman et al., 2020). As operational emissions steadily decrease due to technological advances and cleaner energy systems, embodied impacts are becoming increasingly dominant.

To standardize the assessment of lifecycle impacts, the European standard EN 15804 and ISO 21930 have introduced a modular structure that organizes lifecycle impacts into product stages (A1–A3), construction stages (A4–A5), use stages (B1–B7), EOL stages (C1–C4), and benefits or burdens beyond the lifecycle (module D), as it is shown in Table 2-1. This structure has become widely adopted in Environmental Product Declarations (EPDs) and building regulations because it provides consistency in defining system boundaries and comparing material impacts (Durão et al., 2020). Modules A1, A2, and A3 collectively define the product stage, covering raw material extraction, transport to manufacturing, and manufacturing processes, while module A4 characterizes transportation of materials to the construction site.

Transportation of materials, represented in module A4 of the LCA framework, can contribute between 5% and 30% of total embodied carbon depending on supply chain configuration, transportation distance, and material mass. This shift has placed significant attention on early stage decisions, including supply chain logistics and construction product sourcing (Barbhuiya & Das, 2023).

Despite the recognized value of LCA, one of the persistent challenges in construction research and practice is the availability and suitability of LCA databases. Environmental databases often vary in regional relevance, methodological transparency, and completeness. Mismatches between database assumptions and project specific conditions can introduce significant uncertainty, particularly when databases originate from regions with different industrial processes, energy mixes, or construction practices (Lasvaux et al., 2015). These limitations underscore the need for critical evaluation of available datasets and careful selection of appropriate sources.

2.5.1 Transport Impacts in Circular Construction and Deconstruction Systems

The relevance of transport modelling becomes even more pronounced within CE strategies, particularly in deconstruction and material reuse systems. Reverse logistics require that salvaged components be transported from demolition or deconstruction sites to sorting hubs, refurbishment plants, or new construction projects. These flows mirror the forward A4 stage, with similar sensitivities to distance, load mass, vehicle characteristics, and fuel type. Studies by Coelho et al. (2013), Ajayi et al. (2017), and Brandao et al. (2022), emphasize that transport logistics are often the determining factor in whether reuse systems deliver net environmental benefits. Long travel distances for reclaimed materials can offset the carbon savings gained by avoiding new manufacturing. For this reason, the spatial configuration of hubs and facilities is a critical design parameter in RSC planning for circular construction.

Table 2-1 Building Life Cycle Stages

Stage name	Stage	Description
Production Stage	A1	Raw Material Extraction
	A2	Transport to Manufacturing Site
	A3	Manufacturing
Construction Stage	A4	Transport to Construction Site
	A5	Construction/ Assembly
Use Stage	B1	Use
	B2	Maintenance
	B3	Repair
	B4	Replacement
	B5	Refurbishment
	B6	Operational Energy Use
	B7	Operational Water Use
EOL Stage	C1	Deconstruction and Demolition
	C2	Transport
	C3	Waste Processing
	C4	Disposal
Benefits and Loads Beyond System Boundary	D	Reuse, Recovery and/or Recycling Potentials, Expressed as Net Impacts and Benefits

Lifecycle transport impacts within A4 are commonly quantified using one of three methodological approaches: fuel-based assessment, ton-kilometer activity factors, or distance-based emission factors. The ton-kilometer method is the most widely used in LCA studies and aligns with ISO 14083, which standardizes greenhouse gas accounting for transport services. Emission factors vary by truck class, payload efficiency, driving cycle, and regional fuel characteristics. Studies from

Canada and Europe frequently apply heavy duty truck emission factors in the range of 60 to 90 g CO_2 per ton-kilometer for diesel vehicles, although values differ depending on modelling assumptions (Berglund et al., 2021; X. Pan et al., 2020).
Module A5 includes impacts associated with on-site construction activities, including installation processes, equipment operation, and fuel consumption by machinery. In projects involving significant material handling, demolition, or heavy equipment use, A5 can represent a meaningful portion of total embodied emissions, even if it typically remains smaller than A1–A3. Studies such as Barbhuiya & Das (2023) highlight the growing significance of A5 as construction practices expand their use of specialized machinery and complex site operations.
In the context of circular deconstruction, reverse transport sequences often account for a substantial share of embodied carbon, which means that transport modelling and hub location optimization directly affect the environmental feasibility of reuse strategies.

2.6 Modular and Off-site Construction

The construction industry is undergoing a significant transformation, shifting from traditional on-site practices to off-site, manufacturing style production. Off-site construction offers numerous advantages, including accelerated project completion, enhanced quality control, reduced lifecycle costs, improved health and safety standards, and minimized waste generation (Obi et al., 2022). However, despite these benefits, the adoption of off-site practices has not met expectations. Various factors, including market maturity, contextual drivers, and perceived risks among project stakeholders, have contributed to this slow transition (Sutrisna & Goulding, 2019).
A persistent obstacle to broad adoption is the historical perception held by many stakeholders, including architects, engineers, contractors, and clients. Modular methods are frequently viewed as a temporary or expedient solution, primarily suited for emergency or rapid deployment scenarios, such as post-war rebuilding or natural disaster recovery (Cao et al., 2015). This perception inhibits the long-term capital investment and process development necessary for industrializing the sector.
Prefabrication and modular construction are two primary methods of off-site construction (Assaad et al., 2022). Prefabrication involves manufacturing building components (such as walls, floors, and ceilings), in controlled factory environments before transporting them to the construction site for assembly. Modular construction, on the other hand, entails the production of fully pre-engineered, standardized modules that can be assembled on-site with minimal modifications. Both approaches enhance construction efficiency by improving quality control, reducing waste, and optimizing safety measures (Dams et al., 2021).
Beyond these operational benefits, modular construction presents a viable solution to several challenges in the construction industry, including supply chain disruptions and labor shortages. Additionally, modular projects are well-suited for urban environments where space constraints limit material storage and on-site preparation (Bertram et al., 2019). By standardizing, streamlining, and automating key segments of the value chain, modular construction transforms buildings into product-like entities rather than traditional projects (Obi et al., 2022). As the industry

advances, valuable insights can be drawn from the manufacturing sector, emphasizing the importance of platform based product design to enhance scalability and efficiency (Jack S. Goulding, 2019).

The integration of modular construction within the CE has led to the emergence of innovative design principles aimed at maximizing material reuse and minimizing waste. Design strategies such as Design for Manufacturing and Assembly (DfM/A) (Wasim et al., 2022), Design for Circular Economy (DfCE), Design for Reverse Logistics (DfRL), Design for Disassembly (DFD), and DFD/A (ISO, 2020-01) are critical in aligning modular construction with sustainability objectives. DFD/A plays a pivotal role in prolonging the lifecycle of modular components and facilitating their seamless integration into various contexts. DFD/A not only enhances a structure's utility throughout its initial lifecycle but also allows modular elements to be swiftly repurposed for different applications, thereby increasing efficiency and versatility in building use.

By embracing adaptability principles, the need for excessive demolition and new construction can be reduced. Instead, assets can be remodeled, repurposed, modified, upgraded, or converted to extend their service life and support a wider range of applications. This approach aligns with CE principles by promoting the recovery, reuse, and recycling of deconstructed materials, reducing environmental impact while maximizing economic value.

Early integration of DFD/A principles during the planning and design phases enhances efficiency across all lifecycle stages, from usage and maintenance to EOL procedures. A key aspect of this approach is durability, which determines an asset's ability to function within its environment over a specified period (Hernández, 2025). However, durability and adaptability must be balanced: while a structure may be durable without being adaptable, it risks obsolescence before reaching the end of its intended lifecycle. Conversely, adaptability without durability may compromise long term performance. This interdependence underscores the importance of designing structures that optimize both characteristics, ensuring that buildings remain functional, efficient, and sustainable over time.

2.6.1 Automation in Modular Construction and Deconstruction

One of the key advantages of modular construction is its potential for automation. The controlled factory setting enables greater precision in cutting, assembly, and quality control through the use of automated machinery and robotics (Pan et al., 2022). This automation enhances efficiency, reduces labor dependency, and improves overall productivity in the construction process.

Furthermore, modular construction holds promise for automating the deconstruction process. Since modular components are designed for disassembly, automated systems can be developed to efficiently dismantle, separate, and salvage valuable materials and components (Dams et al., 2021). This innovation has the potential to revolutionize the RSC by enabling more systematic and cost-effective recovery of building materials.

However, despite these advancements, several challenges remain. The absence of harmonized standards and dimensional compatibility across prefab manufacturers remains a significant barrier to effective component reuse. (Razkenari et al., 2020). Additionally, the successful implementation of robotics and automation in modular construction requires a sustainable level of demand to justify the associated investment costs (M. Pan et al., 2020). Overcoming these challenges necessitates the development of a well-structured FSC and RSC that facilitates the seamless integration of modular components into both new construction and deconstruction processes.

2.7 Deconstruction and Disassembly

Implementing a CE perspective in the construction sector is increasingly recognized as an effective response to the escalating volumes of construction and demolition waste (Brandão et al., 2021). Although the concept of deconstruction, defined as the systematic dismantling of buildings to recover materials, components, and elements for high value reuse, has been acknowledged for decades, industry uptake has lagged because workable, scalable models were lacking. Conventional demolition still dominates EOL practice, and, as illustrated in Figure 2-2, recycling remains the principal route for most CDW streams. Only a limited set of easily removable elements such as windows frames and doors are commonly salvaged for direct reuse (Bertino et al., 2021; Tingley & Davison, 2011).

Recent technological advances, notably in prefabrication and modular construction, are beginning to change this landscape. Modular elements are designed for efficient assembly, disassembly, and reclamation, thereby easing the recovery of valuable components at EOL and aligning with CE principles (Eberhardt et al., 2022). Nevertheless, legacy structures built without disassembly in mind still pose significant challenges to widespread deconstruction.

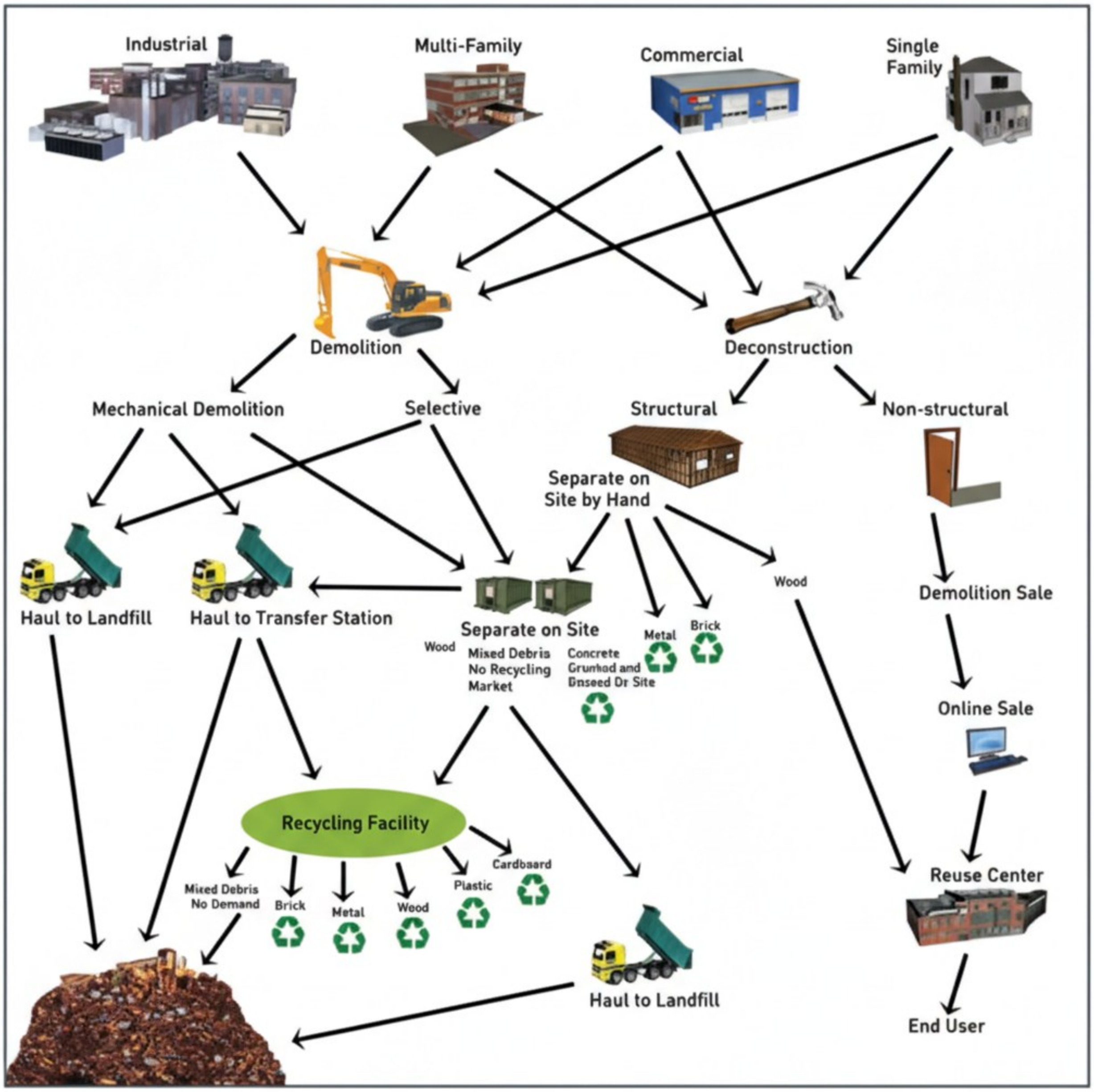


Figure 2-2 Current demolition and deconstruction process (Adapted from (Zelechowski, 2012))

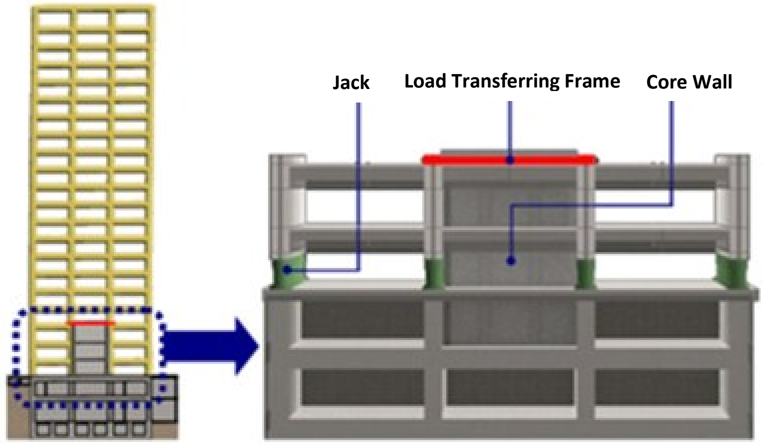
2.7.1 Modular Components in Deconstruction

While prefabrication and modular construction are not new concepts, they are attracting renewed interest and investment as advances in digital design, manufacturing automation, and supply chain optimization lower costs and increase precision. The adoption of modular techniques enables the off-site fabrication and on-site assembly of standardized building components that can be efficiently disassembled and repurposed in future projects (Rios et al., 2015).

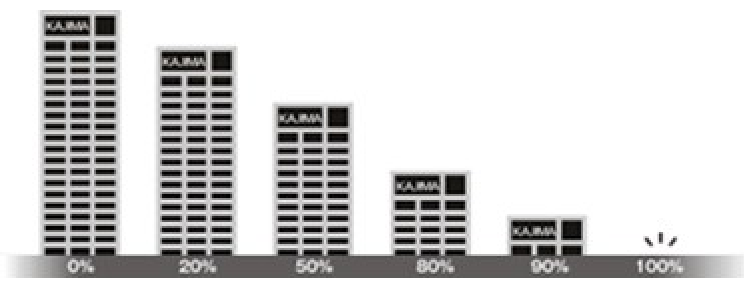
Disassembly represents a more efficient approach than conventional selective deconstruction because entire modules, whether volumetric units or panelized elements, can be lifted out intact, transported with minimal breakage, and reinstalled with limited refurbishment. This minimally intrusive process shortens program schedules, reduces labor hours, and lowers overall cost, while simultaneously curbing waste generation and mitigating on-site dust and noise. In many instances components require little or no repair prior to reuse, provided their condition has been documented and monitored throughout the service life (O'Grady et al., 2021).

The inherent adaptability of modular assemblies also enables staged remodeling, repurposing, and structural adaptation long before a building reaches its nominal EOL. By embedding identifiers such as DPPs in each component, stakeholders can track provenance, maintenance records, and performance data, expediting certification and marketplace matching for secondary use. Such data rich tracking is expected to accelerate the transition toward a circular construction economy by enhancing material and energy efficiency, extending product lifespans, and optimizing design, production, utilization, and EOL management (Adisorn et al., 2021).

Japanese contractors have developed industrialized deconstruction systems that demonstrate how high-rise dismantling can be executed safely, quickly, and with substantial material recovery. One of the most prominent examples is the Kajima 'Cut-and-Take-Down' (CTD) method. Kajima CTD method. Figure 2-3(b) shows that CTD technique is a top-down, floor-by-floor dismantling system engineered for high-rise buildings in dense urban environments. The operation begins with the installation of a fully enclosed, telescopic scaffold and noise-shielding roof deck at the top of the structure. Heavy demolition machinery and self-climbing hydraulic jacks are positioned on the uppermost floor, as it is shown in Figure 2-3(a). Within the sealed enclosure, structural members are sequentially cut, crushed, and sorted; crushed concrete, reinforcing steel, and reusable components are transferred via temporary internal elevators or chutes to ground level processing zones. Once a floor has been completely cleared, the hydraulic jacks lower the entire work platform, hoist, and scaffold assembly by one floor, and the cycle repeats until the building is dismantled to ground level (Lee et al., 2015).



(a) Strategic position of hydraulic jack in CTD technique



(b) Gradual reduction in the height of building

Figure 2-3 Kajima cut and take down (CTD) technique (Adapted from (Kajima, 2024))

The environmental, labor, and time benefits of the CTD system are significant. Because all dismantling activities occur inside an enclosed "box" dust, noise, and vibration emissions are reduced by up to 90% compared with conventional high-reach demolition, thereby minimizing disturbance to surrounding communities and lowering the project's carbon footprint (Ahn et al., 2013). Material separation at source achieves reported recycling or reuse rates exceeding 85%, as steel sections, facade panels, and mechanical equipment are extracted intact and routed directly to secondary markets. Labor safety is enhanced because workers operate on a stable, level deck with perimeter fall protection, and the need for external cranes is largely eliminated. Although CTD requires meticulous planning and can take 10–15% longer than explosive or high-reach demolition, overall project schedules remain competitive due to concurrent processing and reduced off-site waste handling. Moreover, the high salvage rate yields economic returns that partly offset extended on-site durations (Noboru, 2021).

2.8 Supply Chain in Construction Industry

The integration of advanced supply chain management (SCM) principles within the realm of off-site construction and subsequent deconstruction projects represents a necessary paradigm shift in the construction domain. Unlike traditional, site-centric methods, industrialized construction fundamentally requires the adoption of well-established operational research principles typically found in manufacturing sectors (Zaalouk et al., 2023). Cultivating an orderly and seamless supply chain, complete with a meticulous delineation of each participant within the material and activity continuum, holds immense potential for advancing modular construction in both the production (forward) and EOL (reverse) phases (Masood et al., 2021). The maturity of the forward flow directly dictates the feasibility and economic viability of the reverse flow.

2.8.1 Forward Supply Chain (FSC) in Modular Construction

FSC in modular construction encompasses the flow of raw materials through fabrication facilities, manufacturing of modular components, transport logistics, and final on-site assembly. Despite the innovative potential inherent in modular construction, its widespread popularity within the global industry has been hampered by systemic challenges, notably limited awareness, insufficient domain knowledge, and, critically, the absence of a robust, mature supply chain network (Masood et al., 2022).

Unlike established construction methods, modular construction requires an intensely coordinated network of specialized manufacturers, component suppliers, integrated transportation services, and skilled site assemblers for seamless execution. The current fragmentation and immaturity of this network result in inefficiencies, delays, escalated costs, and compromised quality, which actively discourage industry participation.

Logistical operations within the modular construction industry are currently grappling with issues that arise directly from the sector's relative immaturity (Hsu et al., 2019). Compared to the highly refined logistics practices in traditional manufacturing, the modular construction supply chain lacks the sophistication required to efficiently transport and deliver volumetric components.

A core logistics constraint is the transportation complexity resulting from the varied size and geometry of modular components. Since many components and modules are oversized compared to standard shipping containers, this variability forces reliance on specialized heavy-haul transport (Zhang et al., 2024). This requirement increases planning complexity, necessitates obtaining excessive regulatory permitting for large loads, and fundamentally prevents the realization of economies of scale associated with standardized, intermodal global freight logistics.

The lack of consistent component standardization in an immature modular FSC leads directly to non-optimized transport solutions. This, in turn, imposes a high regulatory and cost burden, acting as a structural impediment to the widespread commercial scaling of modular construction (Peiris et al., 2022). The resulting increase in operational costs and lead times contributes significantly to market resistance against embracing modular approaches at scale.

Storage presents another significant challenge within the modular construction supply chain. This complexity is exponentially increased by the intrinsic potential for component reusability. Unlike conventional construction materials, which are often classified as disposable waste after a single building use, modular components are designed to be disassembled and potentially reassembled or refurbished multiple times (Almashaqbeh & El-Rayes, 2022). This demands adaptive and sustainable storage solutions that are capable of maintaining component longevity and ensuring their quality and structural integrity over potentially extended periods of inventory holding. The successful preservation of this residual value is a non-negotiable prerequisite for viable reverse logistics planning.

The inherent fragmentation in conventional construction, where design, manufacturing, and assembly are typically handled by distinct, uncoordinated entities, is poorly suited for modular approaches. Table 2-2 shows a comparison between traditional site built SCM and modular construction FSC requirements.

Table 2-2 Comparison of Traditional Site Built SCM vs. Modular Construction FSC Requirements

Supply Chain Characteristic	**Traditional Site Built SCM**	**Modular Construction FSC Requirement**
Production Environment	Uncontrolled site conditions, labor intensive	Controlled factory environment, automated processes
Material Variability	High; procurement often localized and customized	Low; standardization of components required
Logistics Focus	JIT (Just-in-Time) delivery of raw materials	JIT delivery of finished, large volume components
Quality Control	Site inspection and post-installation validation	Factory gate inspection, precise tolerances
Network Integration	Fragmented, sequential subcontracting	Highly integrated, collaborative manufacturing network

Drawing lessons from global examples provides a path forward for overcoming the systemic constraints outlined above. The Japanese company Sekisui House provides a highly refined model for industrialized housing, successfully demonstrating scalable modular construction through deep operational control and systemic integration, as shown in Figure 2-4 (Modcoach, 2025). Sekisui House emerged in Japan to address post-war housing shortages and rapidly adapted to increasingly strict seismic and insulation standards. This history fostered a shift toward scalable prefabrication, moving beyond simple product substitution to a sophisticated, service-oriented prefabrication model that incorporates advanced building delivery and extensive post-occupancy services.

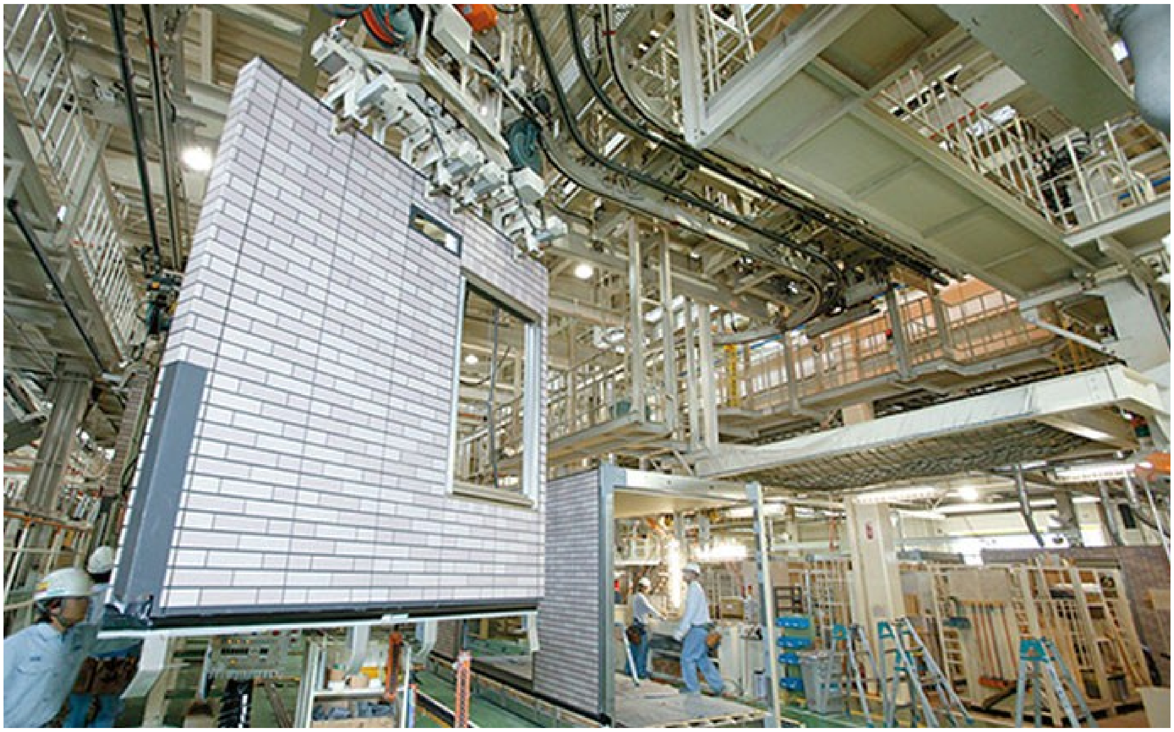


Figure 2-4 Example of modular construction in Sekisui House company (Adapted from (Modcoach, 2025))

Sekisui House's success is rooted in its strong vertical integration, which effectively counters the fragmentation common in the modular construction industry. By designing and manufacturing its own structural systems, finishes, and building components, the company maintains full control from initial design to on-site assembly. This minimizes dependence on external suppliers and reduces supply chain risks, while ensuring the precision and consistency needed for large scale, high quality production (Modcoach, 2025).

Additionally, Sekisui House aligns its FSC with CE principles. High quality, durable components, supported by long term warranties and maintenance programs, are manufactured using DfD principles, preserving residual value over time. As a result, EOL disassembly becomes practical and economically viable, allowing components to be reused or recycled. The company's commitment to achieving complete recycling of construction waste further demonstrates its advanced closed loop system (Chau et al., 2024).

To fully integrate modular construction into the deconstruction process, the establishment of an effective RSC model is essential. This model ensures the efficient flow and utilization of modular components throughout their lifecycle, from initial assembly to eventual deconstruction and reuse. Table 2-3 shows the gap in the research associated with RSC and prefabricated construction concepts.

Table 2-3 Review of reusing material/component with different methods of dismantling buildings

Article	Deconstruction/ Disassembly	Material Reuse	Component Reuse	Prefabricated Construction
(Hopkinson et al., 2018)	Disassembly		*	*
(Ginga et al., 2020)	Deconstruction	*		
(Tingley & Davison, 2011)	Deconstruction	*		
(Boukherroub et al., 2024)	Deconstruction	*		
(Derikvand & Fink, 2023)	Deconstruction	*	*	*
(Brandão et al., 2021)	Deconstruction	*		
(Rios et al., 2015)	Disassembly		*	*
(Benachio et al., 2020)	Disassembly		*	*
(Rahla et al., 2021)	Disassembly	*	*	*
(Yang et al., 2025)	Disassembly		*	*
(Walsh & Shotton, 2024)	Disassembly	*	*	
(Minunno et al., 2018)	Disassembly		*	*
(Nasir et al., 2017)	Deconstruction	*		
(Sormunen & Kärki, 2019)	Deconstruction	*		

The studies summarized in Table 2-3 indicate that buildings constructed using modular and prefabricated methods offer greater potential for the recovery and reuse of components at the end of their lifecycle. These studies demonstrate that such building types are inherently more suitable for disassembly compared to conventional deconstruction or demolition approaches. Furthermore, the findings suggest that disassembly significantly increases the likelihood of extending the service life of building components through reuse, rather than limiting recovery to material recycling. In contrast, recycling processes typically involve additional energy consumption, time, and labor, thereby reducing the overall environmental benefits.

2.8.2 Reverse Supply Chain (RSC) in Construction Industry

Historically, the construction industry has adhered to a linear economic model, characterized by the discard of materials at the end of their lifecycle (Nasir et al., 2017). This is primarily because conventional buildings are typically assembled for a single use lifecycle and lack embedded design features that facilitate component reuse.

The concept of the RSC offers a remedial strategy by salvaging components from decommissioned buildings and reintroducing them into the value chain for recovery, refurbishment, and reuse (Minunno et al., 2018). While the underlying factors driving the adoption of sustainable practices in RSC are globally recognized, the effectiveness of any circular model hinges on the ability to quantify the strength of these drivers (Yi et al., 2016). This quantification is crucial for prioritizing efforts and tangibly enhancing long term sustainability outcomes.

The systemic shift away from the traditional linear model, where materials are used once and discarded, requires the formal establishment of the RSC. The RSC is essential for modern construction, providing the structured framework necessary to reintroduce salvaged components into the economic value chain through processes of recovery, refurbishment, and reuse (Minunno et al., 2018).

The emergence of deconstruction, which involves the careful dismantling of buildings to salvage valuable materials and components, has brought the absence of a comprehensive and practical RSC into sharp focus. Without a well-established and efficient RSC infrastructure, the full potential of deconstruction to support sustainable resource recovery and reuse remains largely untapped.

The industry is currently implementing an RSC that incorporates CE principles, primarily focusing on the management of CDW (Brandao et al., 2022). This approach employs a reverse logistics strategy, typically within the context of traditional construction, addressing materials at a bulk level (e.g., concrete, steel scrap) rather than focusing on the recovery and reuse of complex modular components (Sormunen & Kärki, 2019). Figure 2-5 illustrates the current state of the RSC within contemporary deconstruction practices, indicating the specific stage at which current efforts are concentrated. At present, the process largely focuses on recovering materials rather than whole components, reflecting the industry’s limited progress in developing a fully established and systematic approach for component level reclamation.

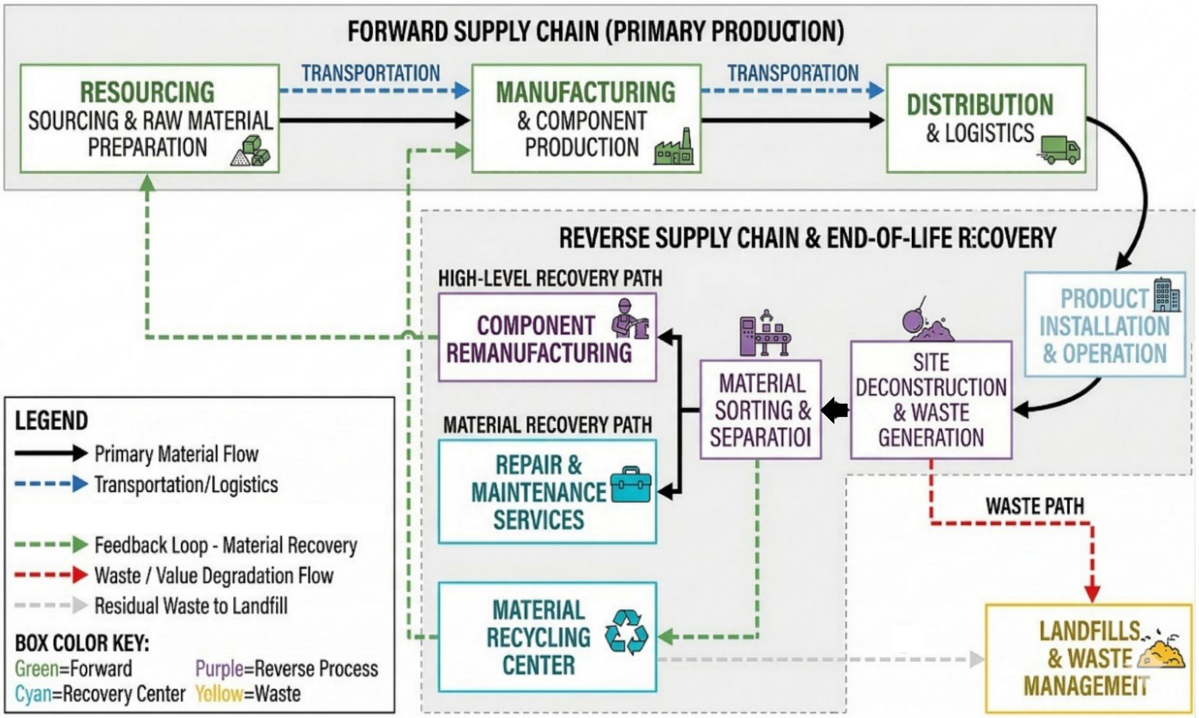


Figure 2-5 Current RSC of deconstruction at material and component level

A comprehensive RSC focuses on the efficient flow of reusable materials and components from EOL structures back into the production cycle. It necessitates establishing infrastructure and processes for the collection, detailed sorting, and reintegration of reusable or recyclable assets obtained through deconstruction.

A robust RSC structure plays a critical role in addressing market resistance to off-site construction methods, particularly concerns related to the deconstruction phase. By ensuring a managed and value generating EOL process, the RSC mitigates environmental and disposal risks while enhancing the overall circularity and sustainability of the construction sector (Peiris et al., 2022). Realizing these benefits, however, requires dedicated infrastructure capable of handling the variable inflow and outflow of components throughout a building's lifecycle. Such infrastructure must support both the RSC and the reverse flow embedded in the CE model. Central to this system are strategically located hubs, which facilitate compatibility of components for reuse, and efficient material movement, key conditions for unlocking the full lifecycle advantages of modular construction in both construction and deconstruction phases.

2.9 Supply Chain and Challenges of Steel Reuse

The development of an efficient supply chain for steel reuse in deconstruction projects faces several critical challenges as it mentioned before. These challenges span across deconstruction practices, hub operations, supply-demand coordination, and policy-related limitations.

2.9.1 Quality of Deconstructed Components

Deconstruction represents a fundamental stage in enabling steel reuse; however, it is associated with several operational and technical constraints, as mentioned in Section 2.7.1. The selection of appropriate deconstruction techniques (Rios et al., 2015) and methods significantly influences both cost and material and component recovery efficiency. Compared to conventional demolition, deconstruction is often more labor-intensive and costly, which may limit its adoption. Additionally, quality inspection is required to detect potential damage to steel components after deconstruction, ensuring their suitability for reuse (Bertino et al., 2021).

A key process in this stage is the deconstruction audit (or pre-demolition audit), defined as a systematic assessment conducted prior to demolition to identify, quantify, and evaluate materials for reuse, recycling, or safe disposal. This process supports circular construction practices by facilitating material recovery, reducing waste, and improving environmental compliance (Eberhardt et al., 2022). Techniques such as selective deconstruction further enhance the ability to recover high-quality reusable components.

2.9.2 Hub Availability

Hub facilities, which function as intermediate points for storage, processing, and redistribution of reclaimed steel, currently lack well-defined operational frameworks for establishing hubs. In many cases, these hubs act similarly to stockholders; however, their roles, processes, and standards remain insufficiently formalized. The absence of standardized reuse guidelines, such as design codes for reclaimed steel components, further complicates their operation.

Moreover, the integration of hubs within the broader supply chain remains limited (Hsu et al., 2019). The economic viability of steel reuse projects is highly sensitive to market conditions, particularly the volatility of new and scrap steel prices. This uncertainty introduces financial risks that are difficult to predict. Additional costs associated with reclaimed steel, including deconstruction, repairing, transportation, storage, and quality testing, are highly variable and project-specific, further affecting profitability (Zhang et al., 2024).

2.9.3 Supply and Demand Matching

One of the major challenges in steel reuse is the effective matching of supply and demand. This involves identifying potential end-users and aligning supply with demand in terms of location, timing, and material and component specifications such as type and dimensions. Inefficiencies in any of these aspects can significantly increase costs and reduce feasibility.

Barriers to effective matching include the limited availability of reclaimed steel component, lack of traceability, and time constraints (Almashaqbeh & El-Rayes, 2022). A critical issue is the absence of reliable information regarding the origin, mechanical and chemical properties, and service history of reclaimed components (Peiris et al., 2022). This lack of data hinders confidence among designers and contractors and complicates the safe and efficient reuse of steel components.

To address these challenges, the implementation of MPs (Adisorn et al., 2021) can facilitate tracking and information management throughout the material lifecycle. In addition, the use of BIM can support the identification of components within existing structures, including their properties, certifications, and testing records, thereby improving transparency and enabling informed decision-making (Liu et al., 2015; Pan & Zhang, 2023).

2.9.4 Incentives and Policy Limitations

Policy and regulatory frameworks currently provide limited support for steel reuse practices. There is a lack of effective incentives to encourage the adoption of reused materials and components, such as carbon credits or tax benefits (Askar et al., 2021). As a result, companies are often not sufficiently motivated to prioritize reuse over conventional recycling or the use of new components (Benjamin et al., 2022).

Economic barriers further constrain adoption, as the additional costs and uncertainties associated with reclaimed steel are not adequately offset by existing policies. In particular, the recovery of steel for reuse, as opposed to recycling, is not strongly incentivized within current legislative frameworks. Strengthening policy support and introducing targeted incentives are therefore essential to promote the wider implementation of steel reuse in the construction industry.

2.10 Genetic Algorithms (GAs)

An Evolutionary Algorithm (EA) is a key concept underlying Genetic Algorithm (GA) theory. Evolutionary algorithms are now widely recognized as a powerful tool for solving complex optimization problems (Gen & Cheng, 1999), such as those encountered in logistics and supply chain management (Reeves & Rowe, 2002). These algorithms are inspired by the principles of natural evolution and employ mechanisms such as selection, crossover, and mutation to iteratively improve a population of candidate solutions. The use of selection, crossover (recombination) and mutation are central to the metaphor of biological evolution in GAs. These mechanisms work together to evolve a population of candidate solutions over successive generations. Below is a breakdown of each operator and how they inter-relate.

Many studies emphasize the importance of maintaining a balance between exploration and exploitation in optimization algorithms. In this context, the comparative analysis presented in Table 2-4 highlights the relative performance of classical methods, such as Linear Programming (LP) and Mixed-Integer Linear Programming (MILP), and metaheuristic approaches, including Simulated Annealing (SA), Particle Swarm Optimization (PSO), and the GA. While classical methods provide exact solutions, they are often limited by scalability and their reliance on linearity and strict mathematical formulations (Lambora et al., 2019). Similarly, alternative metaheuristics such as SA and PSO demonstrate strengths in local search and rapid convergence, respectively; however, they may suffer from limited exploration capabilities or premature convergence, particularly in discrete and combinatorial problems such as facility location.

Table 2-4 Comparative summary of optimization methods for facility location problems

Method	Type	Key Strengths	Key Limitations	Suitability for Facility Location	Overall Assessment
Linear Programming (LP)	Classical	Provides exact optimal solutions; computationally efficient for linear problems	Requires linearity and continuous variables; cannot handle discrete decisions effectively	Low, facility location is inherently discrete and often nonlinear	Not suitable for realistic large-scale problems
Mixed-Integer Linear Programming (MILP)	Classical	Handles discrete/binary decisions; yields exact solutions	Computationally expensive for large-scale problems; requires simplifications	Moderate, applicable but becomes intractable as problem size increases	Limited scalability for complex supply chains
Simulated Annealing (SA)	Metaheuristic	Simple implementation; good local search capability	Single-solution based; slow convergence; limited global exploration	Moderate, can solve, but may miss better global solutions	Less robust for complex networks
Particle Swarm Optimization (PSO)	Metaheuristic	Fast convergence; easy to implement	Prone to premature convergence; less effective for discrete variables	Moderate, better for continuous problems than discrete facility decisions	Not ideal for combinatorial structure
Genetic Algorithm (GA)	Metaheuristic	Handles discrete variables naturally; strong global search; flexible with constraints; scalable	Requires parameter tuning; no guarantee of exact optimum	High, well-suited for combinatorial, large-scale, and constrained problems	Most suitable and robust choice

In contrast, GA demonstrates superior adaptability by effectively balancing global exploration and local exploitation through its population-based search and genetic operators. Many studies emphasize the importance of this balance. Recent work has also analyzed how crossover contributes to search speed compared with mutation-only algorithms. For example,(Lambora et al., 2019) demonstrated that conventional steady-state genetic algorithms operate approximately 25% faster than standard evolutionary algorithms that rely solely on bit mutation. Their findings further indicate that larger population sizes can enhance convergence speed compared to very small populations. In addition, (Zhang et al., 2007) conducted an in-depth examination of crossover operators across several well-known combinatorial optimization problems, showing improved performance compared to mutation-only approaches.

2.10.1 Selection

Selection is the process by which a subset of individuals (candidate solutions, or “chromosomes”) is chosen from the current population to serve as parents for producing the next generation. The guiding principle is “survival of the fittest”, better-performing individuals (according to the fitness function) which have a higher chance of being selected. For example, roulette wheel selection, tournament selection and rank-based selection are typical schemes (Shukla et al., 2015). The purpose of selection is two-fold: exploit the good solutions found so far (by giving them more reproduction potential) and apply selection pressure so the population gradually shifts toward better fitness regions.

2.10.2 Crossover (Recombination)

Crossover is the operator that takes two (or sometimes more) parent chromosomes and combines their genetic material (i.e., parts of the solution encoding) to produce offspring (Umbarkar & Sheth, 2015). The idea is that parents with good features can combine those features, producing new solutions that might inherit the strengths of both (Hasançebi & Erbatur, 2000). For example, in a binary-encoded GA, one-point crossover may select a random locus and swap sub-segments between parents.

The crossover operator serves primarily the exploration of the search space by combining different promising building-blocks from the population. However, it does not by itself introduce new genetic material, it only recombines what is already present.

2.10.3 Mutation

Mutation is the operator that introduces random changes into offspring (or sometimes into members of the population). These random changes may take the form of flipping a bit, swapping two genes, adding or subtracting a value, depending on the encoding. The purpose of mutation is to maintain genetic diversity in the population, prevent premature convergence, and allow the algorithm to explore new regions of the search space that crossover alone may not reach (Lambora et al., 2019). Mutation thus supports exploration and helps the algorithm avoid getting trapped in local optima.

2.10.4 Interaction Among Operators and Implications for Optimization

In practice, these operators work together in each generation of the GA roughly as follows:

- Evaluate the fitness of each individual in the population (according to the objective function).
- Select a subset of individuals based on their fitness (selection).
- Recombine (crossover) selected parents to form offspring.
- Mutate some of the members of the offspring to introduce variation.
- Replace fully or partially the current population with new individuals (offspring and possibly survivors from the previous generation).

- Repeat until a stopping criterion (e.g., number of generations, time, fitness threshold) is met.

Maintaining an appropriate balance between exploration and exploitation is essential for achieving effective performance in GAs (Lambora et al., 2019). Exploitation focuses on intensifying the search around high-quality solutions by favoring their selection and recombination, allowing promising characteristics to be preserved and refined through crossover operations. In contrast, exploration aims to diversify the search space and prevent premature convergence by introducing new genetic material, a role primarily fulfilled by mutation. Together, these mechanisms enable the algorithm to efficiently search for near-optimal solutions while avoiding stagnation in local optima.

2.11 Genetic Algorithm (GA) and Geographic Information Systems Integration

In the context of circular deconstruction, logistics management plays a pivotal role in ensuring the efficient recovery, transportation, and redistribution of materials. The adoption of GAs has gained significant traction in the construction industry, particularly for optimizing logistics and decision-making in CE models (Gen & Lin, 2023). As traditional construction methods transition toward more sustainable approaches, the integration of GA has proven instrumental in addressing complex real-world challenges. Hybrid approaches that combine GA with other digital technologies, such as GIS, have been increasingly proposed to enhance spatial decision-making and optimize resource allocation (Jauhar et al., 2021). The integration of GA with GIS is particularly beneficial for tracking the flow of reclaimed materials and components throughout the logistics system, offering enhanced visibility, spatial intelligence, and control over deconstruction processes (Irizarry et al., 2013; Song et al., 2017). When coupled with BIM, this integration further supports the visualization and management of deconstructed components, providing a comprehensive view of the circular supply chain (Zhang et al., 2016).

2.12 Summary and Conclusions

This literature review examined key research streams related to the adoption of CE principles in the construction industry, with a focus on material and component recovery at building EOL. Existing studies highlight the construction sector's significant environmental impact and the potential of circular strategies, such as reuse, deconstruction, and modular design, to reduce waste and extend material lifecycles. However, current practices remain largely oriented toward recycling and downcycling, with limited emphasis on high-value component reuse.

Research on MFA and LCA demonstrates the importance of understanding material stocks, embodied emissions, and transportation impacts. In particular, transportation and supply chain configuration are shown to play a critical role in determining both environmental and economic performance in circular construction systems. While modular and off-site construction methods support disassembly and reuse, the lack of standardization and interoperability among modular components significantly constrains their reuse potential.

From a systems perspective, the literature reveals that conventional construction supply chains are not designed to manage reclaimed components effectively. Although RSC are recognized as essential for circular construction, existing models are fragmented, poorly coordinated, and often focused on waste handling rather than value retention. This limits the practical implementation of component reuse at scale.

To address the complexity of circular construction networks, recent studies increasingly employ optimization and computational methods. GAs particularly when integrated with GIS, are shown to be effective for solving complex facility location and allocation problems by incorporating spatial, logistical, and demand-related factors. Despite these advances, there remains a clear gap in integrated, hub-based, and data-driven RSC frameworks that support component reuse.

These gaps underscore the need for an optimized, spatially explicit RSC model that connects deconstruction sites, processing and refurbishment activities, storage, and end-users. Next chapters are directly addressing this need by proposing a GIS-integrated optimization framework to support efficient and sustainable component reuse in the construction industry.

Chapter 3. Methodology

3.1 Introduction

This chapter presents the methodological framework adopted to address the hub location and allocation problem within RSC for deconstructed building components. GA is employed as the primary optimization technique due to the combinatorial nature of the problem and its ability to efficiently balance exploration and exploitation. The proposed approach integrates GIS-based spatial data, transportation distances, demand volumes, and capacity constraints to identify cost-efficient and feasible system configurations. Through an iterative evolutionary process, the GA searches for near-optimal solutions that support the development of an effective and sustainable RSC network.

3.2 Proposed Method

In the proposed framework, hubs play a pivotal role in addressing the challenges of an underdeveloped market and the imbalance between supply and demand. Hubs serve as multifunctional facilities where key processes take place, including storage, quality testing, repair, refurbishment, and decision-making regarding the destination of disassembled components as shown in Figure 3-1. In this figure, there are five nodes in our proposed model, deconstruction sites (DS_j), factories (F_l), recycle centers (RC_m), hubs (H_k) and new buildings or end-users (U_n). Table 3-1 indicates these nodes and their indices.
The number of each of these five nodes are the input of the GA algorithm. Hubs play the rule of the supplier for the other four demand nodes (DS, F, RC, U) and provide them services and supplies related to reusable deconstructed building components.

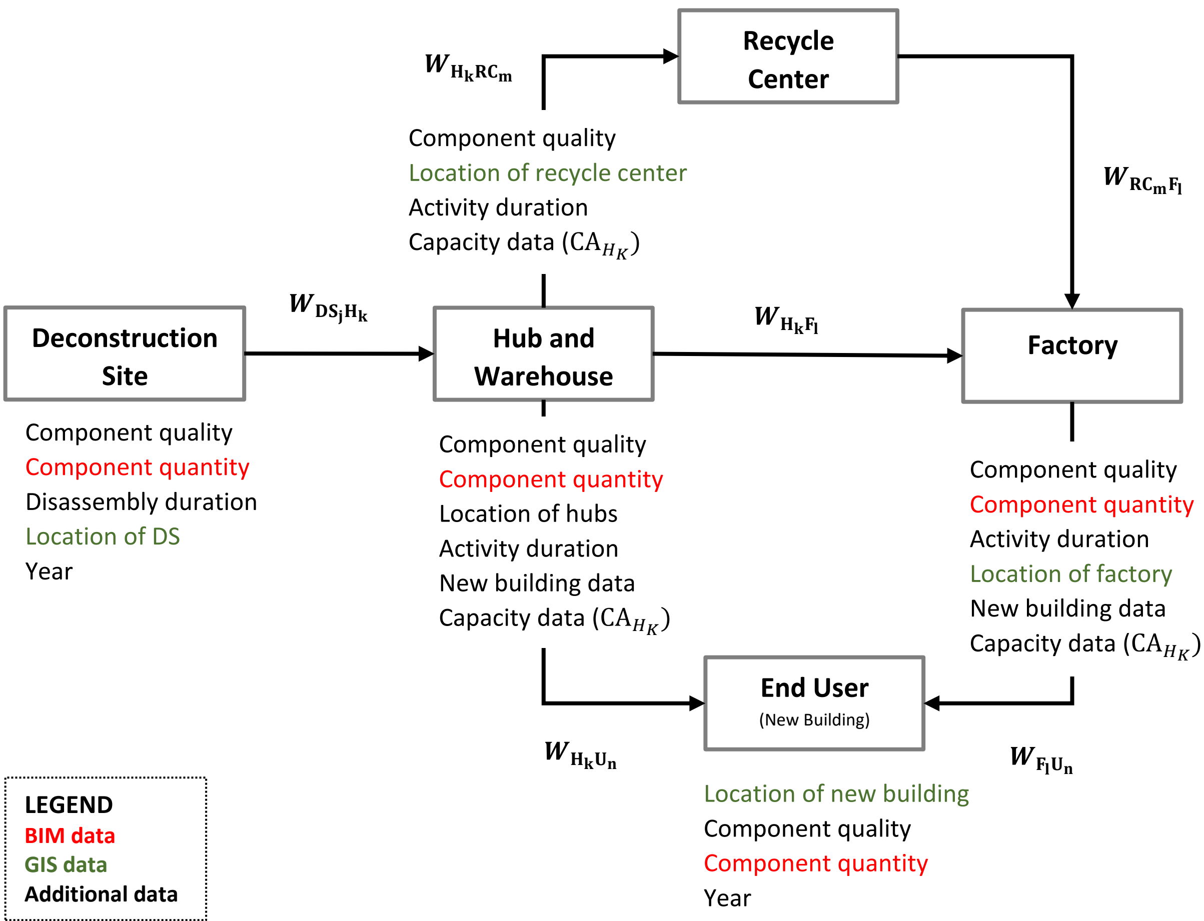


Figure 3-1 Five primary nodes in the data flow

Table 3-1 Main nodes and indices

Abbreviation	**Node Type**	**Associated Parameter/ Index**	**Description**	**Range**
DS	Deconstruction Site	j	Number of deconstruction sites	$\forall j \in (1 \ldots J)$
H	Hub	k	Number of hubs	$\forall k \in (1 \ldots K)$
RC	Recycle Center	m	Number of recycle centers	$\forall m \in (1 \ldots M)$
F	Factory	l	Number of factories	$\forall l \in (1 \ldots L)$
U	New Building (End User)	n	Number of end-users	$\forall n \in (1 \ldots N)$

The loads transported to the various nodes are also illustrated in this figure. Two key data inputs essential for the optimization model are the transportation costs and the distances between nodes, as well as the quantities of load movement among them. A detailed description of these factors is provided in Table 3-2.

Table 3-2 Loads and transportation cost between nodes in the RSC model

Category	Notation	Description
Component Flow (Load)	$W_{DS_jH_k}$	Loads from Deconstruction Site *j* to Hub *k*
	$W_{H_kU_n}$	Loads from Hub *k* to End-User *n*
	$W_{H_kF_l}$	Loads from Hub *k* to Factory *l*
	$W_{F_lU_n}$	Loads from Factory *l* to End-User *n*
	$W_{H_kRC_m}$	Loads from Hub *k* to Recycling Center *m*
	$W_{RC_mF_l}$	Loads from Recycling center *m* to Factory *l*
	W_{U_n}	Total loads transported to the End-User n
Transportation Cost (CA$)	$T_{DS_jH_k}$	Cost from Deconstruction Site *j* to Hub *k*
	$T_{H_kF_l}$	Cost from Hub *k* to Factory *l*
	$T_{H_kRC_m}$	Cost from Hub *k* to Recycling Center *m*
	$T_{RC_mF_l}$	Cost from Recycling center *m* to Factory *l*
	$T_{F_lU_n}$	Cost from Factory *l* to End-User *n*
	$T_{H_kU_n}$	Cost from Hub *k* to End-User *n*

Different types of data are required for the two stages of this model. The first stage is to find the optimal location for the hubs based on long-term prediction of supply and demand of reused steels. The second stage is to create the RSC operational model based on existing hubs to track the flow of the components in each step and node based on the detailed input data.

To find the optimal location for hubs, the data from GIS is needed to estimate the distance between different nodes and to detect paths. Simultaneously, the capacity (CA_{H_K}) of each hub can be established by correlating the floor area of each potential hub locations with construction cost limitation, which informs decisions regarding structural parameters such as the number of floors. Then the data related to the volume of weight/load transported from each node can be calculated using data extracted from 2D BIM or estimated based on the data from available sources such as the estimates based on the floor area of each selected structure (DS_j).

At the operational modeling stage, RSC can utilize 3D BIM and MPs to gather precise data on the geometry, age, and physical condition of components. The availability of such detailed models allows for the specific identification of deconstructable components, thereby facilitating the selection of optimal deconstruction methods. Using these detailed models allows for a better understanding of component quantities and states. This information can be used to optimize the total cost of the RSC. Also, detailed data is pivotal for minimizing transportation related CO_2 emissions and optimizing the total cost of the model. However, capturing such data is challenging right now. These aspects are explained in details in Section 3.4.

Ultimately, our proposed model posits that hub effectiveness is governed by two factors: location and hub operation. Strategic placement is required to minimize logistical and operational costs, while diverse hub functionalities ensure that components are processed effectively prior to reintroduction into the supply chain.

3.3 Location Optimization

To identify optimal hub locations, GA (NSGA-II) is employed to optimize all potential connections between demand nodes, DS, F, RC, U, and H nodes in MATLAB platform. DS, F, RC and U are called demand nodes in this study since they all depend on hub as a supply node. This optimization focuses on two critical factors: the demand of each node and their distance from the hubs. In our model, these factors are represented as the transportation cost ($T_{DS_jH_k}$, $T_{H_kU_n}$, $T_{H_kF_l}$, $T_{H_kRC_m}$) and the weight of components transported between these nodes and hubs ($W_{\mathrm{DS_jH_k}}$, $W_{\mathrm{H_kF_l}}$, $W_{\mathrm{F_lU_n}}$, $W_{\mathrm{H_kRC_m}}$, $W_{\mathrm{RC_mF_l}}$), as explained in Table 3-2. In this table, the factor representing the total load transported to the end-user (W_{U_n}) serves as a balancing parameter that ensures consistency between the total input and output loads of the components in the model. This factor is used for model validation, as it verifies mass balance across the system and confirms the internal consistency of the proposed framework (see Section 3.4 for further details).

Furthermore, the broader model encompasses the transport of components between recycle centers and factories ($W_{\mathrm{RC_mF_l}}$) and the flow from factories to the end-user ($W_{\mathrm{F_lU_n}}$). However, this optimization framework focuses on the variables that directly influence hub location decisions. While the aforementioned flows contribute to the total cost function of the proposed model, they are spatially invariant regarding the optimal placement of hubs. Consequently, this chapter restricts its scope to those factors that directly constrain and define the optimization model.

The decision-making process prioritizes demand nodes based on their significance, determined by the volume of demand they generate. Higher demand implies a greater volume of deconstructed components to be transported, thereby increasing the priority of those nodes. Consequently, hub locations are adjusted to minimize transportation costs by positioning them closer to high priority demand nodes. This approach ensures that the hub placement aligns with the most critical needs of the model, optimizing efficiency and resource allocation.

3.4 Solution Approach

To optimize the location selection, GA optimization approach was used for its proven effectiveness in solving multi objective problems, such as facility location optimization, where the solution space is very large, and traditional optimization methods often face significant limitations (Celik Turkoglu & Erol Genevois, 2020). The robustness of the GA in exploring and exploiting the search space with input data from GIS enables it to identify near optimal solutions efficiently, making it an ideal choice for this problem.

3.4.1 GIS Data Integration and Spatial Parameters

This study utilizes GIS to identify and spatialize demand nodes, categorized as DS, F, U, RC alongside potential hub locations.

The data extraction process involves three primary layers:

Land-Use and Building Information: Spatial layers (urban, industrial, and residential) are sourced from open-data portals to identify candidate sites. Attributes such as gross floor area, building age, and number of floors are extracted to estimate material potential.

Site Feasibility: Potential hubs and end-user nodes are filtered based on parcel-level vacancy data and cadastral registers. For a location to be considered a viable hub, it must meet a minimum handling capacity (e.g., 5,000 tons), estimated through industrial land-use classifications and warehouse throughput rates.

Network Analysis: Rather than using Euclidean distance, this model employs a GIS-based network analysis tool. By utilizing a routable road graph (derived from OpenStreetMap), the model incorporates real-world constraints such as speed limits and weight restrictions to calculate the most cost-efficient truck-based transportation routes.

3.4.2 Material Load Estimation and Flow Dynamics

A significant challenge in RSC modeling is the accurate estimation of deconstructed loads, as historical data for salvageable steel is often unavailable. This methodology addresses this gap by calculating the steel intensity per unit area. To estimate the volume of movement throughout the model, the following factors are applied:

Extractable Steel Calculation: The total load at deconstruction sites is estimated by applying a steel weight ratio (ranging from 0.05 to 0.08 tons per square meter) to the gross floor area of the targeted structures.

Salvageability and Construction Logic: Since existing buildings were not originally designed for deconstruction, the amount of reusable steel is estimated based on regional construction codes and the year of assembly. These factors provide a proxy for the structural connections used, which dictates the percentage of steel that can be salvaged with minimal repair.

Component State and Flow Allocation: The condition of components upon arrival at a hub determines their subsequent flow. Components requiring advanced refurbishment are directed to F nodes, while those that are structurally compromised are diverted to RC.

End-User Demand Prediction: Demand nodes (DS, F, RC, U) are assigned demand profiles based on market trends. Given that end-users represent the primary recovery pathway, the model allocates the highest demand percentage to these nodes, targeting vacant industrial lands or facilities slated for redevelopment within a long-term (50-year) horizon.

The details about real-world geometric data and the calculated component loads in this study is fully explained in the Chapters 4 and 5.

3.5 Decision Variables, Chromosome Representation and Search Space

The primary decision variables in this model are the hub assignments for each demand node. These variables are directly encoded in the chromosome structure, based on demands, load weight, hub capacities, and distances. Additionally, binary decision variables are implicitly represented, if no demand nodes are assigned to a potential hub location, it is not considered as a place to build a hub.

Each chromosome in the GA represents a potential solution to the hub location problem. The chromosome is encoded as a vector of length A, where “a” is the number of demand nodes (DS, F, RC, U). Each element of the chromosome corresponds to the demand nodes and contains an integer value representing the index of the hub to which each node is assigned. This encoding ensures that the assignments of demand nodes to hubs are explicitly represented, allowing the GA to explore various configurations of hub-demand node assignments.

For each demand node, there are K possible hubs they can be assigned to, as shown in Figure 3-2. Since there are “A” demand nodes (J+ L+ M+N = A), and each one can be assigned independently to any of the K hubs, the total number of possible combinations (i.e., the size of the search space) is: K^A

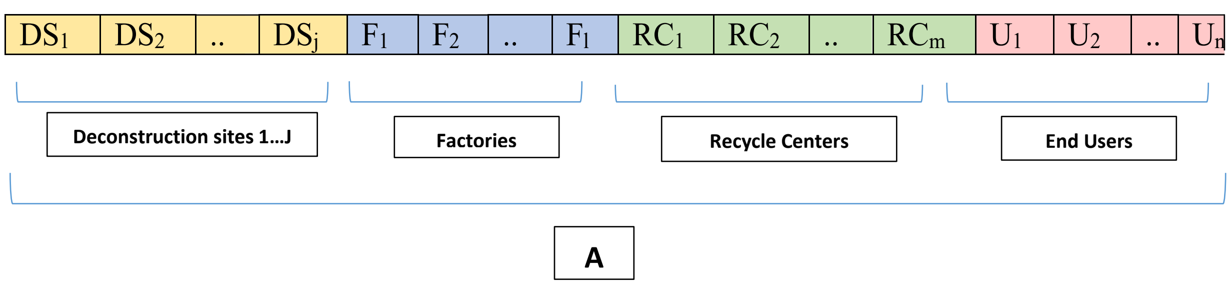


Figure 3-2 Structure of a chromosome

3.6 Objective Function and Constraints

The objective function is designed to minimize the total cost, which is calculated as the sum of transportation costs between all nodes. The transportation cost is computed as the product of the distance between a node and the assigned hub and the weight of the transported components (Equation (1)). The goal of the GA is to minimize this cost function by evolving the population of chromosomes over successive generations. Table 3-2 shows the variables used in the Equation (1) along with the description. Loads and costs are given in ton and CA$, respectively.

$$\begin{aligned} \min Z = & \left(\sum_{j=1}^{J}\sum_{k=1}^{K} T_{DS_jH_k} \times W_{DS_jH_k} \times \propto_{jk}\right) + \left(\sum_{k=1}^{K}\sum_{m=1}^{M} T_{H_kRC_m} \times W_{H_kRC_m} \times \propto_{km}\right) \\ & + \left(\sum_{k=1}^{K}\sum_{l=1}^{L} T_{H_kF_l} \times W_{H_kF_l} \times \propto_{kl}\right) + \left(\sum_{k=1}^{K}\sum_{n=1}^{N} T_{H_kU_n} \times W_{H_kU_n} \times \propto_{kn}\right) \end{aligned} \quad (1)$$

In Equation (1), $\propto_{jk}$ $\propto_{km}$ $\propto_{kn}$ $\propto_{kl}$ are binary variables and equal to one if nodes DS_j, F_l, RC_m, U_n are assigned to hub k, and 0 otherwise. It is assumed that each node is assigned to only one hub, which is represented by: $\propto_{jk}+\propto_{km}+\propto_{kn}+\propto_{kl}=1$

After the optimal locations of the hubs (k) are located, we can estimate the CO_2 emission rate in this RSC model as shown in Equation (2) below.

$$ET = \left[\begin{aligned} & \left(\sum_{j=1}^{J}\sum_{k=1}^{K} T_{DS_jH_k} \times W_{DS_jH_k} \times \propto_{jk}\right) + \left(\sum_{k=1}^{K}\sum_{m=1}^{M} T_{H_kRC_m} \times W_{H_kRC_m} \times \propto_{km}\right) \\ & + \left(\sum_{k=1}^{K}\sum_{l=1}^{L} T_{H_kF_l} \times W_{H_kF_l} \times \propto_{kl}\right) + \left(\sum_{k=1}^{K}\sum_{n=1}^{N} T_{H_kU_n} \times W_{H_kU_n} \times \propto_{kn}\right) \end{aligned}\right] \times EF \quad (2)$$

The new variables in Equation (2) includes ET, which is the transportation CO_2 emission and EF, the truck CO_2 emission factor which is equal to about 63–66 g CO_2 per ton-kilometer (Zubair et al., 2023).

The constraints of Equation (1) are as follow:

Equation (3) shows the constraint that the total load received by an end-user must equal the sum of loads from hubs and factories. Where W_{U_N} is the total loads to end-users.

$$\sum_{n=1}^{N} W_{U_n} = \sum_{k=1}^{K} W_{H_kU_n} + \sum_{l=1}^{L} W_{F_lU_n} \quad (3)$$

Equation (4) shows that a node *a* can only be assigned to hub *k* if hub *k* is established. β_k is a binary variable, where $\beta_k = 1$ if a hub is built at potential location *k*, and 0 otherwise.

$$\propto_{ak} \leq \beta_k \qquad \forall a,k \tag{4}$$

Equation (5) shows that the total loads from DS_j assigned to one hub cannot exceed its capacity. CA_{H_k} is the capacity of the hub k.

$$\mathrm{CA_{H_k}} \times \beta_k \geq \sum_{j=1}^{J} \mathrm{W_{DS_jH_k}} \times \propto_{jk} \tag{5}$$

Equation (6) shows the limitation on the number of hubs that can be built at the potential locations.

$$\sum_{k=1}^{K} \beta_k \leq H_{max} \tag{6}$$

Equation (7) shows that the loads from deconstruction sites must equal the sum of loads sent to end-users, factories, and recycling centers.

$$\sum_{j=1}^{J} W_{DS_jH_k} = \sum_{n=1}^{N} W_{H_kU_n} + \sum_{m=1}^{M} W_{H_kRC_m} + \sum_{l=1}^{L} W_{H_kF_l} \tag{7}$$

Chapter 4. Conceptual Framework for Component Reuse RSC

4.1 Introduction

The emergence of deconstruction, which involves carefully dismantling buildings to salvage valuable materials and components, has brought the absence of a comprehensive and practical RSC into sharp focus. Without a well-established and efficient RSC infrastructure, the full potential of deconstruction for sustainable resource recovery remains largely untapped. The RSC must focus on the efficient flow of reusable materials and components from EOL structures back into the production cycle, establishing infrastructure and processes for the collection, detailed sorting, and reintegration of recoverable assets. By promoting standardization, compatibility, and efficient material flow, a robust RSC enhances the overall circularity and sustainability of the construction sector, unlocking the full potential of modular construction throughout its entire lifecycle.

4.2 The Flow of Material and Components After Deconstruction

After identifying optimal locations for hubs and warehouses, an understanding of material and component flows is essential. The RSC within the deconstruction industry is depicted in Figure 4-1, illustrating the updated flow of materials and components. This representation refines the current deconstruction supply chain, specifically capturing the unique aspects of the RSC in modular construction after disassembly at a deconstruction site. Central to this process is the active hubs, which serve as the primary nodes for component management. At these facilities, various quality tests are conducted to assess the current state of components, informing decisions on repair, prefabrication, remanufacturing, or recycling within the hub's operational scope.

Unlike other models of the RSC which mentioned in Section 2.8.2, this model places the hub as a pivotal factor. This strategic positioning enables a more accurate analysis of components and enhances the ability to salvage more disassembled parts for reuse. Our new model Figure *3-1* facilitates cost minimization, encompassing deconstruction, refurbishment, logistics, and design adjustments. Additionally, it contributes to the reduction of CO_2 emissions, both embodied and from transportation, while simplifying the process, especially in terms of re-certifying reused components.

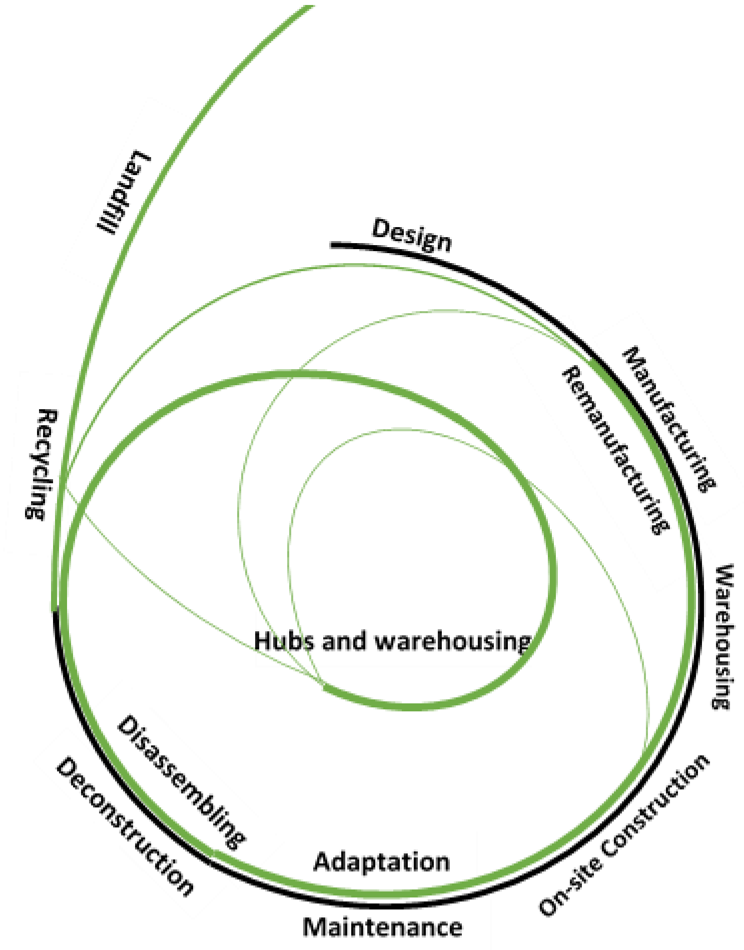


Figure 4-1 Forward and proposed RS in construction and deconstruction

4.3 Digital Integration and Data Requirements for the Circular RSC

The transition to CE in the construction sector fundamentally depends on comprehensive data integration to improve deconstruction, reuse, and recycling planning. Different types of data play key roles in understanding and optimizing the EOL and reuse potential of building components.

BIM models and blueprint data provide detailed information about the composition and condition of structures. This specificity is crucial for supporting accurate EOL assessments and helping to identify which materials and components can be efficiently recovered. The use of digital technologies and BIM (Section 2.4) is pivotal in enabling an efficient RSC by facilitating the documentation and traceability of modular components. BIM based digital twins ensure accurate tracking of component history and condition, which helps identify components that can undergo multiple reuse cycles.

Design methods and adaptability data are also essential for extending building lifecycles. Modular and flexible construction allows easier disassembly and component replacement, promoting partial renovations instead of full demolitions. Furthermore, material data and deconstruction methods influence the feasibility of recovery, with materials like steel and timber often offering higher reuse rates than reinforced concrete. Integrating these datasets enables predictive evaluations of recovery costs, environmental impacts, and technical challenges which is illustrated in Table 4-1.

Table 4-1 Data and their application in RSC model

Data / **Application**	**BIM/ Blue Print**	**Building Type (commercial, residential, industrial…)**	**Design Method (Modularity Percentage)**	**Type of materials**	**Stage of life**	**Adaptability Level**	**Deconstructed buildings (Method)**
EOL Assessment	*	*	*	*	*	*	*
Adaptation and Lifecycle Extension		*	*	*	*	*	*
Deconstruction Feasibility	*	*	*	*		*	*
Multiple Lifecycle Possibility for material and component		*		*	*	*	*
Stakeholder Collaboration	*	*		*	*		*
Market Assessment (To Reuse)	*		*	*		*	*
Reverse supply chain Model			*	*		*	

Effective collaboration among stakeholders, architects, engineers, contractors, and recyclers, relies on shared BIM environments for transparent data exchange and coordinated planning.

4.4 Strategic Logistics: Modeling the Role of Hubs

RSC modeling connects deconstruction sites with reuse centers like hubs by utilizing integrated data on material types, building characteristics, and deconstruction methods. The absence of dedicated logistics hubs in the deconstruction process for deconstructed components is a crucial missing link between the highly variable supply of recovered components and the specific, often standardized, demand for reuse.

The establishment of hubs and warehouses emerges as a viable solution to facilitate a seamless circular supply chain. Sustaining this circularity hinges on the symbiotic relationship between demand and the availability of reusable components. Achieving this equilibrium necessitates a demand rate that matches or surpasses the supply. Moreover, the availability of such components is contingent upon three pivotal factors: the appropriateness of the product (including standardization levels, quality, and service life), minimized waiting times, and strategically positioned hubs located within a reasonable proximity.

To establish a hub, a well-defined model is required to illustrate its functions and operational processes. The flowchart presented in Figure 4-2 illustrates the movement of components within the facility, outlining the decision-making process based on component condition and detailing how the hubs operate at each stage of the workflow.

At the deconstruction site (DS), modification is applied during disassembly for inspection and quality assurance, selecting the best deconstruction methods that do not compromise the integrity of disassembled parts.

After quality assurance, a pre-quality test at DS will decide whether these parts are deconstructed without losing their original form and good enough to be repaired or they were demolished and cannot be salvaged, if so, they will be transported to RC ($SC_i^t = 0$). Following the pre quality control at DS, a more precise quality control, including non-destructive testing (NDT), is implemented in the hub. In this phase, separation is done more accurately, if a component is repairable ($SR_i^t = 1$), if will stay at hub, or it is unrepairable and needs to be transported to a recycle center. After deciding the reusability of a component, a specialized quality control assesses the functions required for the component, determining if it needs major repair ($SRM_i^t = 0$), and must be transported to the factory for remanufacturing or if refurbishing and repairing can be carried out at the hub. The state and condition of components in each stage is summarized in Table 4-2.

Table 4-2 State of components in different stages inside the hub

Variable	State of Component	Value
SC_i^t	Demolished	0
	Deconstructed	1
SR_i^t	Unrepairable	0
	Repairable	1
SRM_i^t	Remanufacturing needs	0
	Do not need remanufacturing	1

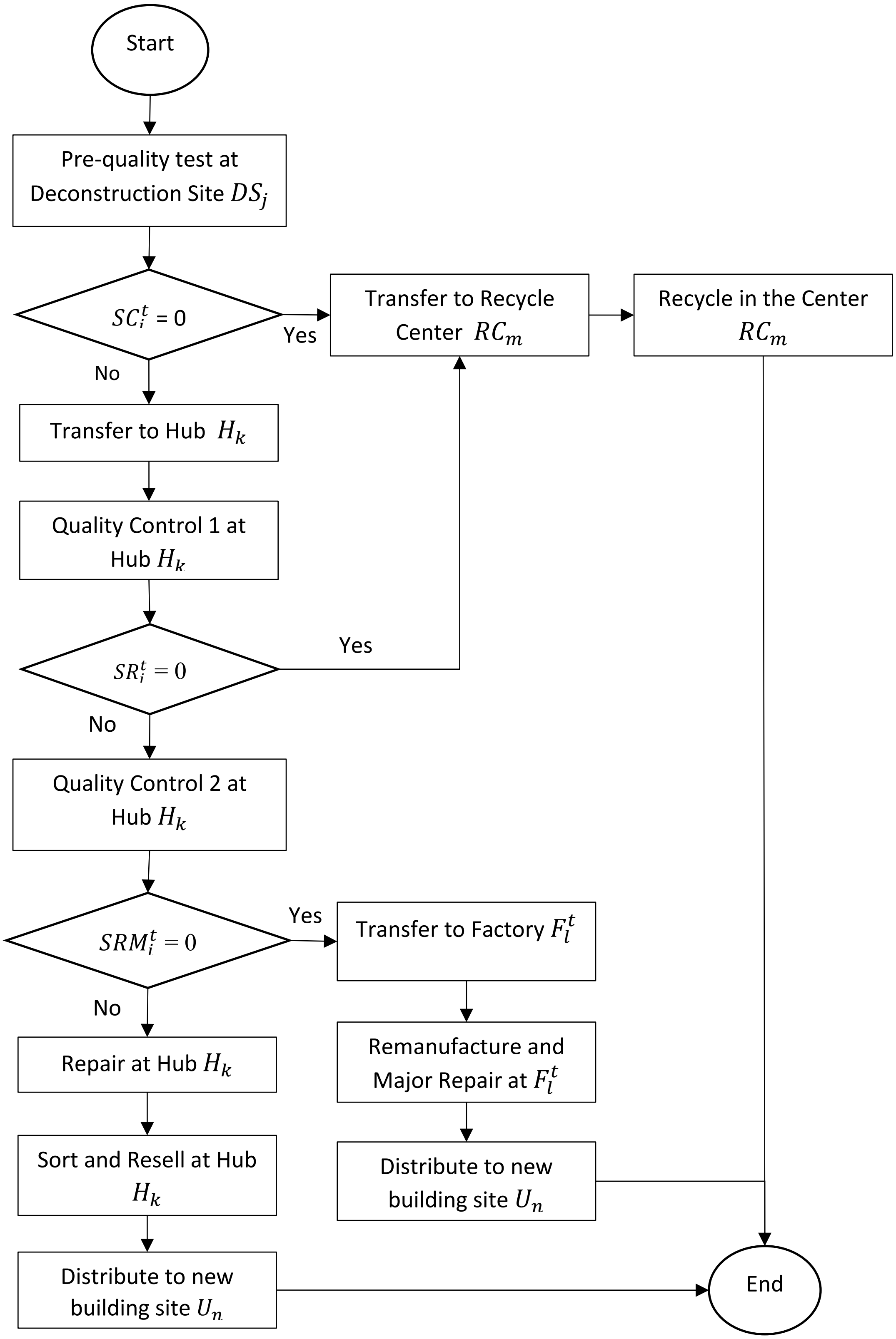


Figure 4-2 Flow of components in a hub, based on their state and condition

4.5 Cost Factors in Reverse Logistics

Accurately estimating the associated costs is a prominent challenge in connecting the FSC with the RSC within the prefabrication process. Market assessments benefit from data integration, as the economic feasibility of reuse depends on both component quality and market demand; for instance, structural components often hold higher resale value, whereas interior finishes, though highly reusable, may offer lower financial returns.

Several influential factors can impact these costs, including:

- Cost of deconstruction/disassembly.
- Cost of pre-quality test at the sites.
- Cost of components (quality, age, degree of standardization).
- Cost of transportation from the deconstruction site to hubs.
- Cost of transportation from the deconstruction site to factories and recycle centers.
- Cost of quality testing and certification.
- Cost of adjusting and repairing.
- Cost of refurbishment.
- Cost of warehousing and inventory management.
- Cost of transportation from the hub to the new project site.

4.6 Operational Functions of the Hubs

The primary role of the RSC hub is to normalize the variable output from deconstruction sites into certified, market ready inventory. These centralized facilities must serve as essential coordination centers, bridging the gap between supply and demand and ensuring seamless connectivity among all stakeholders. The suggested process for hubs revolves around four key functions, ensuring salvaged components retain high residual value and remain viable for multiple use cycles.

Table 4-3 outlines the key operational functions of reuse hubs within a circular supply chain for modular and prefabricated construction components. The table demonstrates that reuse hubs act as critical enablers for component recovery, quality assurance, and reintegration into new construction projects, thereby addressing several technical, logistical, and market-related barriers associated with component reuse.

The first function, collection, sorting, and quality control, highlights the role of hubs as centralized facilities for managing salvaged modular components. Notably, quality assessment is conducted through a two-stage evaluation process. As it mentioned before in Figure 4-2, an initial pre-quality assessment takes place at the deconstruction or disassembly site prior to transportation. During this preliminary inspection, components are evaluated to determine whether they are suitable for recovery and transport to the hub or whether they are irreparably damaged and should instead be directed to recycling facilities. Components that pass this initial screening are transported to the hub, where a second, more detailed quality control process is performed. At the hub, components are systematically inspected, tested, and categorized based on their condition, performance, and reuse potential. This two-tier quality control system reduces unnecessary transportation, minimizes handling of non-recoverable components, and significantly lowers the perceived risk associated with reused construction elements.

The second function, inventory management, emphasizes the role of hubs in bridging the temporal gap between component supply and construction demand. Salvaged components often become available at times that do not coincide with new project schedules. Reuse hubs address this mismatch by maintaining structured inventories supported by databases or digital catalogues that record component specifications, quantities, condition levels, and availability. Effective inventory management enhances transparency, improves planning reliability, and increases the accessibility of reusable components for designers and contractors, thereby facilitating their integration into future construction projects.

The third function, refurbishment and Quality Assurance (QA), reflects the technical decision-making role of hubs in determining the appropriate recovery pathway for each component. Based on the outcomes of the quality control assessments conducted at the hub, components may follow different processing routes (Figure 4-2). Components requiring minor repair, cleaning, or upgrading can be repaired directly at the hub. However, components that require more extensive or specialized refurbishment are transferred to manufacturing or industrial facilities equipped with advanced repair and upgrading capabilities. In cases where components are found to be severely damaged or technically unsuitable for reuse, they are redirected to recycling centers. These decisions are made during the quality control phase and are critical to optimizing resource efficiency, minimizing unnecessary processing, and ensuring that only components meeting performance and safety requirements re-enter the construction supply chain.

The final function, redistribution and demand management, positions reuse hubs as active intermediaries between verified supply and market demand. Once components have been approved for reuse, hubs facilitate their redistribution to relevant stakeholders, including architects, engineers, contractors, and developers. By matching component availability with project-specific requirements, reuse hubs support informed design decisions and promote the practical adoption of reused modular components. This function is essential for closing material loops and ensuring that recovered components are effectively reintegrated into new construction projects rather than remaining in storage or being prematurely recycled.

Table 4-3 illustrates that reuse hubs perform a set of interrelated functions that extend beyond simple collection or storage. Through multi-stage quality control, inventory coordination, refurbishment decision-making, and demand facilitation, these hubs play a central role in enabling circular construction systems. The effective integration of modular and prefabricated construction within a circular economy framework depends on the successful operation of such logistics hubs, as they transform component recovery from a theoretical objective into an efficient and economically viable process. By supporting systematic collection, testing, refurbishment, and inventory management, reuse hubs contribute to reducing material waste, lowering embodied carbon emissions, and enhancing both the environmental and economic performance of construction supply chains.

Table 4-3 Operational functions of reuse hubs within a circular supply chain

Suggested Key Function	Operational Description and Value Proposition
Collection, Sorting, and Quality Control	Hubs would serve as central points for collecting salvaged modular components from deconstruction sites. They facilitate the initial sorting and categorization of components based on their condition, quality, and potential for reuse. This rigorous assessment is crucial for reducing the risk perception associated with reused components.
Inventory Management	Hubs maintain active inventories of available modular components, creating a dedicated catalog or database to track stock. This inventory management system addresses the temporal gap, ensuring components are available when needed for new construction projects.
Repair and QA	Hubs provide the necessary facilities and expertise for refurbishment, repair, updating, and ensuring the quality of the salvaged components. This step is essential to meet current industry standards and ensure the reliability and safety of reused components, maximizing their economic value.
Redistribution and Demand Management	Hubs actively promote the reuse of modular components by connecting the verified supply with project demand. They facilitate the efficient redistribution of components to relevant stakeholders, such as builders and developers, who can integrate them into new construction projects.

4.7 Summary and Conclusion

This chapter provides a roadmap for the proposed RSC by integrating the flow of deconstructed components with the strategic and digital requirements of the network. Central to this model is the operational role of hubs, which function as critical intermediaries whose efficiency is partially dictated by real-time data availability. By modeling these hubs through strategic logistics and analyzing key cost factors, the chapter demonstrates how the state of components, both at the deconstruction site and the hub location, directly governs the movement of components.

Chapter 5. Implementation and Case Study

5.1 Introduction

This chapter evaluates the efficacy of the proposed GA optimization model through a full-scale implementation in MATLAB R2023b and ArcGIS Pro 3.2, focusing on a hypothetical case study of the primary urban corridor in Québec, Canada. By synthesizing spatial data from provincial open-data portals, cadastral registers, and OpenStreetMap (OSM), we identified 91 functional nodes, including deconstruction sites, factories, and recycling centers, across Montréal, Québec City, Sherbrooke, and Trois-Rivières. These cities provide a realistic empirical environment due to their dense industrial zones, supportive building-code amendments, and high material demand. This integrated GIS-based approach allowed for the precise mapping of land-use constraints and truck-based routing distances into the GA's chromosome encoding, ensuring the optimization results reflect actual logistical efficiencies and connectivity requirements for the deconstruction industry.

5.2 Case Study

To evaluate the effectiveness of the proposed GA based hub location optimization model for an RCS, we developed a full-scale implementation in MATLAB R2023b. All spatial data preprocessing and visualization were performed in ArcGIS Pro 3.2, while routing distances were extracted from OSM.

The hypothetical study focuses on four major urban centers in the province of Québec, Canada; Montréal, Québec City, Sherbrooke, and Trois-Rivières (Figure 5-1 shows all nodes in the four focused cities in Quebec Province). These cities were selected for three reasons. First, their combined population exceeds 4.5 million by the year 2025, reported by "Institut de la statistique du Québec", shown in Table 5-1, ensuring a substantial and geographically distributed demand for reclaimed steel components. Second, each metropolitan area hosts extensive industrial zones, providing feasible locations for repair hubs. Third, the adoption of standardized building-code (Ungureanu et al., 2020) amendments and incentive frameworks that explicitly accommodate deconstruction practices enhances the empirical grounding of the model. By aligning with these established regulatory norms, the policy assumptions within the model reflect contemporary industry standards, thereby increasing the validity of its projected outcomes.

Figure 5-1(a) illustrates the spatial distribution of all node types within the network using a color-coded representation. In the figure, green symbols denote hub locations, brown indicates deconstruction sites, pink represents factories, red corresponds to recycling centers, and blue identifies end-user nodes. The figure shows that the majority of hub locations are situated within or in close proximity to the four major cities, reflecting their strategic role in facilitating efficient component flows.

The height of the green columns in Figure 5-1(b) represents the capacity of each hub, enabling a visual comparison of hub capacities assigned to individual cities. In contrast, the heights of columns corresponding to other node types do not represent capacity or demand in a comparable manner and are included solely for visualization purposes; therefore, their relative heights are not meaningful for analysis.

Sherbrooke and Trois-Rivières located between the other major cities contain a greater number of hubs compared to the remaining two bigger cites (i.e. Montréal and Québec City). This allocation is intentional, as their central positions within the network enhance connectivity, improve logistical efficiency, and support smoother component flows across the system.

Furthermore, each hub is labeled with a unique identification number. These identifiers are essential, as they correspond directly to the chromosome encoding used in the optimization model, enabling consistent referencing between the spatial representation and the genetic algorithm framework.

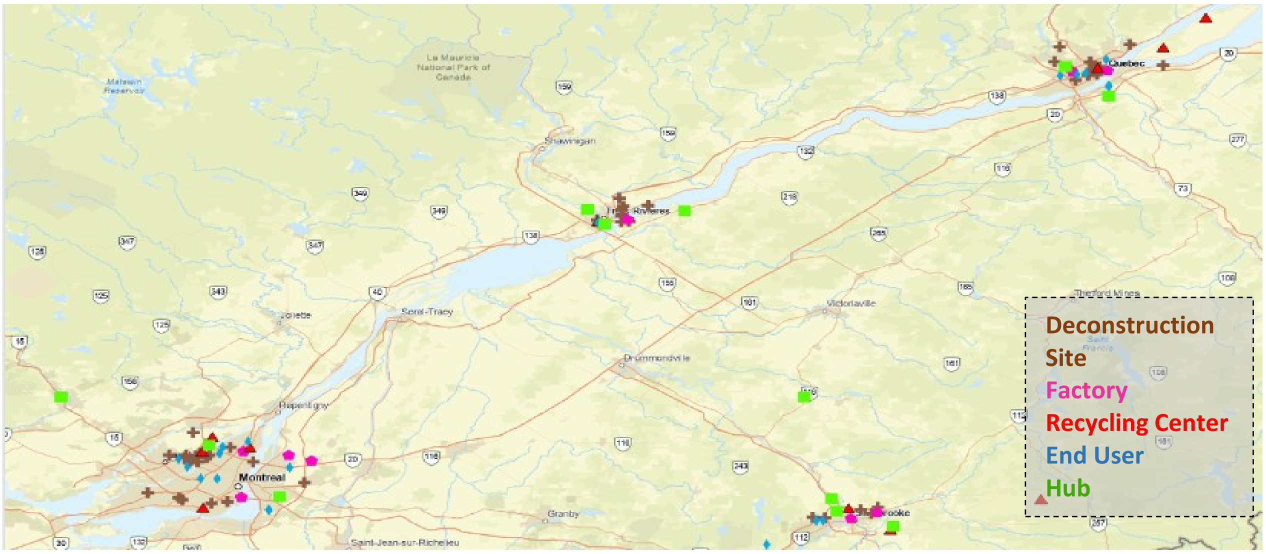
5.3 Data Description

5.3.1 Data Sources

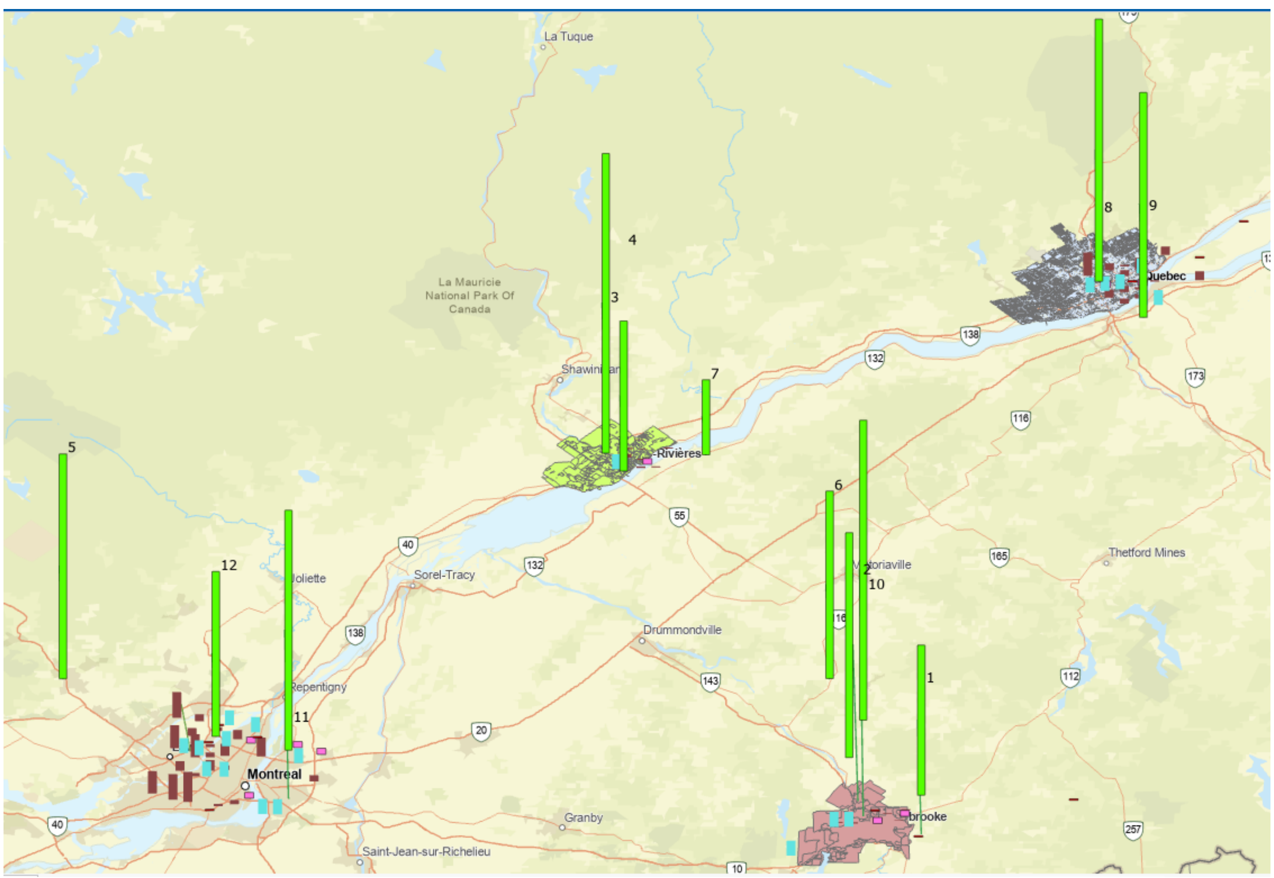
Land Use Data: Spatial land-use layers (urban, industrial, residential, greenfield, and transportation corridors) were downloaded from the Québec government's open-data portal (Québec, 2023) in GeoJSON format. Minor schema inconsistencies were resolved via attribute mapping in ArcGIS. Missing land-use polygons (<1%, means that less than 1% of the land use data in the study area was not originally present in the downloaded GIS datasets), were digitized manually based on high resolution orthophotos supplied by the "Ministère de l'Environnemen de la Lutte contre les changements climatiques de la Faune et des Parcs" (l'Environnement, 2025).

Open Street Map (OSM): A GIS based network analysis was employed to determine transportation routes using the actual road network. The routable road graph, derived from OpenStreetMap (OSM), incorporates real road geometries along with relevant attributes such as speed limits and weight restrictions. The analysis focused exclusively on truck-based land transportation, as rail and inland shipping are generally not used for the transport of steel components in Québec.

Vacancy Land Data: Parcel level vacancy data were collated from the Communauté métropolitaine de Montréal (CMM) and the Communauté métropolitaine de Québec cadastral registers (PDF format). Parcels were evaluated based on their land use and size. Only those with a calculated handling capacity greater than 5,000 tons steel, estimated using typical industrial land-use classifications and average warehouse throughput rates (Ungureanu et al., 2020), were retained as potential hub sites.



(a) Location of all nodes in the Quebec province in GIS map



(b) Location of all nodes and the capacity of hubs

Figure 5-1 All nodes in the four focused cities in Quebec Province

Table 5-1 Population of the four big cities in 2025

City	Great Montréal	Québec	Sherbrooke	Trois-Rivières
Population	2,405,755	592,884	184,303	149,208

5.3.2 Data Characteristics

All spatial data for the network nodes were obtained and processed using ArcGIS, which provided the geographic coordinates and spatial relationships required for the model. In total, 91 functional nodes were modelled: 51 DS_j, 9 refurbishment F_l, 11 RC_m, and 20 U_n, as summarized in Table 5-2. Deconstruction sites correspond to aging steel warehouses larger than 3,000 m², constructed between 1970 and 1990, and identified through municipal building permits and field surveys as buildings likely to be dismantled within the next 50 years. Based on their structural typology (Ungureanu et al., 2020), the recoverable steel quantities from these sites were estimated at 0.05–0.08 $t \cdot m^{-2}$ (Gorgolewski et al., 2010), as mentioned in Section 3.4.2. This total is annualized over a projected 50-year lifespan to determine the yearly volume of recoverable steel components.

Within the RSC network, 9 major steel fabrication plants were considered as factories, representing facilities capable of supporting refurbishment or processing activities prior to component reuse. Additionally, 11 existing metal recycling facilities were included to process materials that cannot be directly reused. Twenty end-users were identified based on the floor area of medium-sized warehouses expected to reach their EOL within the same time horizon, representing potential destinations for reclaimed components.

In addition to these demand nodes, 12 potential hub locations were identified based on the availability of vacant industrial land parcels larger than 1.5 hectares. These hubs function as intermediate facilities within the proposed RSC, where deconstructed components can be inspected, stored, repaired, refurbished, and redistributed to factories, recycling centers, or end-users. ArcGIS was also used to support the estimation of steel quantities from deconstruction sites and the capacity assessment of the potential hub locations.

Table 5-2 Summary of network nodes in the Québec case study

Node type	Symbol	Count	Selection criteria
Deconstruction Site	DS_j	51	Steel warehouses > 3 000 m², built 1970–1990
Factory	F_l	9	Major steel fabrication plants
Recycling Center	RC_m	11	Existing metal recyclers
End User	U_n	20	Warehouses slated for renovation by 2045
Potential hub	H_k	12	Vacant industrial land, area ≥ 1.5 ha

5.3.3 Deconstruction Data

Table 5-3 presents the detailed characteristics of each selected deconstruction site node considered in this study. As described in Section 3.3, each node is assigned a unique identifier corresponding to its position within the chromosome used in the optimization model. The node identifier refers to actual geographic locations selected from among the four major cities identified in Table 5-1, and they represent potential deconstruction sites over the next 50 years, primarily consisting of steel warehouse structures, as summarized in Table 5-2.

To ensure spatial accuracy and data validity, the longitude and latitude of each node are provided. The table also reports the estimated quantity of extractable steel expected from each location, expressed in tons. These quantities are calculated based on the gross floor area of each structure and the assumed steel intensity per unit area. Consistent with the methodology described in Chapters 3 and 5, a steel weight ratio ranging from 0.05 to 0.08 tons per square meter is applied. The corresponding area measurements used in these calculations are also included in the table.

Table 5-3 Deconstruction site nodes data

Node Number	Node Name	Y- Latitude	X-Longitude	Floor Area (m^2)	Total Load of Steel (ton)
1	1000 Boul	45.52069024	-73.37378141	15,268.68	763
2	Entrepot Economique	46.377985	-72.51828	3566.86	178
3	Déménagement Martel Express	46.341355	-72.497511	2914.92	146
4	Club Entrepot Trois Rivières	46.340228	-72.518742	4,432.13	222
5	JCG CENTRE DE TRANSIT	46.358264	-72.518742	8,807.37	440
6	Équipe Bruneau-Côté	46.345865	-72.584067	2,614.96	131
7	Depotium Mini Entrepôt	46.361645	-72.516292	2,449.69	122
8	Entreposage Mauricie	46.39094	-72.446068	2,924.83	146
9	Mini Entrepôt Jolain	46.414027	-72.523641	1,382.21	69
10	Cap de madeleine. Trois riviere	46.38925	-72.513026	1,663.17	83
11	Entrepôt Therrian Warehouses	45.423339	-71.84406	21,580	1165

Node Number	Node Name	Y- Latitude	X-Longitude	Floor Area (m^2)	Total Load of Steel (ton)
12	Canada Post Warehouse	45.443576	-71.826207	27,821.10	1502
13	Mini Entreposage Queen	45.435868	-71.872899	52,440.90	2832
14	Cubicube Entreposage Mobile Inc	45.409843	-71.969029	3,296.25	178
15	Les entrepôts de l'Estrie	45.411771	-72.001988	16441.13	888
16	Logik Inc. Warehouse	46.827863	-71.241013	2,884.19	156
17	Depotium Mini Entrepôt	46.825044	-71.239639	2,519.00	136
18	Entreposage domestique St-Sacrement	46.825983	-71.241013	3,541.98	191
19	Réfrigération Quatre Saisons Inc	46.826923	-71.228653	2,137.03	115
20	StorageMart Mini Entrepôts	46.807188	-71.257492	12,246	661
21	Mini-Entrepôts Méribec	46.803428	-71.235519	10,225	552
22	Hangar - Entrepôts Sécurisés	46.820345	-71.242386	27,650	1493
23	QM, Entrepôt	46.825983	-71.239639	4,845.02	261
24	Entrepôt Le 2800	46.800607	-71.258865	14,340	774
25	Groupe Transrapide	46.831621	-71.056992	51,000	2600
26	Congebec	46.841955	-71.253372	14,254.13	770
27	Équipements d'Entrepôt E3	46.897348	-71.146256	19,721	1065
28	Entreposage MC	46.88984	-71.33577	3,134	170
29	Vanfax Quebec	46.842894	-71.349503	54,935.12	2966
30	Les Entrepôts de l'Habitation	46.818466	-71.306931	18,532	1001

Node Number	Node Name	Y- Latitude	X-Longitude	Floor Area (m^2)	Total Load of Steel (ton)
31	Espaces commerciaux	46.785564	-71.293198	18,615	1005
32	StorageMart Mini Entrepôts	45.652009	-73.625661	8,856	478
33	Entrepôt du Nord Cold storage Inc	45.677921	-73.673726	16,453.40	888
34	Depotium Mini Entrepôt - Laval	45.630886	-73.573475	1,589.33	79
35	Entrepots Frigorifiques Laval Ltée	45.585733	-73.661366	7,812	422
36	S.A.C. 2000 Logistix	45.59246	-73.677846	22,737	1228
37	Entrepotlaval1	45.606873	-73.62978	10,112	546
38	Amazon DYT4	45.599186	-73.697072	50,325.48	2558
39	sunbec food inc entrepot	45.612637	-73.6545	25,300	1366
40	Bureaux	45.606873	-73.692952	18,460	997
41	Centre de distribution	45.599186	-73.63802	3783.32	204
42	Espace Dépot	45.609755	-73.647633	7,500	405
43	Laval warehouse	45.604951	-73.665486	10,700	578
44	Entrepot Frigorifique Deslauriers Inc	45.606873	-73.73827	54,300	2932
45	Entreposage Laval	45.583811	-73.684712	43,525	2350
46	Vention Warehouse	45.47221	-73.712178	40,394.00	2161
47	Entrepôt des Grands Ballets (500)	45.585733	-73.511677	43,907.55	2371
48	Intramodal Warehouses	45.488579	-73.795949	2205.07	119
49	Montreal Sufferance Warehouse Inc.	45.460653	-73.581715	10,022.53	541

Node Number	Node Name	Y- Latitude	X-Longitude	Floor Area (m^2)	Total Load of Steel (ton)
50	Federal Steel Equipment	45.455836	-73.624287	4,860.67	262
51	. Espace entrepôt à louer	45.466992	-73.7034	60,152	3188

After extracting the steel quantity data from each deconstruction site and estimating the average amount of steel expected to become available over the next 50 years, the annual figure was then used to calculate the potential recovery rate within the RSC network. Previous studies indicate that approximately 95% of the extracted steel can be recovered (Pongiglione & Calderini, 2014).

In this case study, the flow of steel components between the different nodes of the RSC network is defined according to the assumptions presented in Table 5-4. It is assumed that about 1% of the extracted components are sent directly to landfills from the deconstruction sites, while the remaining 99% are transported to the hubs. At the hub level, the subsequent routing of components depends on their structural condition (see Section 4.4). Under the assumptions adopted in this model, approximately 65% of the components delivered to the hubs require only minor repair and can therefore be restored within the hub facilities before being transported directly to end-users for reuse. In contrast, around 25% of the components require major repair and refurbishment and are therefore transferred to specialized refurbishment factories before being delivered to the end-users. The remaining 5% of the components are considered unsuitable for reuse even after hub-level assessment and are consequently transported to recycling centers, where they are processed and reintroduced into the supply chain at the material level (see Section 2.3). Finally, the residual portion, comprising approximately 4% of the components and consisting largely of waste and non-steel parts, is transported from the hubs to landfills for final disposal.

Table 5-4 Destination assumptions of extracted steel flow within the RSC

Origin Node	Destination Node	Share of Extracted Steel (%)	Description
Deconstruction site	Landfill	1%	A small portion of extracted components is assumed to be unsuitable for recovery and is directly disposed of.
	Hubs	99%	The majority of extracted steel components are transported to intermediate hubs for inspection, sorting, and further decision-making.
Hub	Direct reuse (to End-Users)	65%	Components requiring only minor repair are restored within the hubs and then transported directly to end-users for reuse.
	Refurbishment factories	25%	Components that require major repair or refurbishment are transported to specialized factories before being delivered to end-users.
	Recycling centers	5%	Components that cannot be reused are transported to recycling centers, where they are processed and reintroduced into the supply chain at the material level.
	Landfill	4%	Residual waste and non-steel parts identified during hub assessment.

5.3.4 Factory Data

Table 5-5 presents the data associated with the nine factory nodes considered in this study. For each factory, geographic coordinates (longitude and latitude) are provided to ensure spatial accuracy in the analysis. As the primary role of this node type is to receive steel components requiring major repair or refurbishment, the key parameter of interest is the quantity of steel transported to these facilities. Accordingly, the analysis estimates the proportion of the total extractable steel from deconstruction sites, Table 5-4, that is expected to be directed to factories for advanced refurbishment processes from hubs. In this study, the quantities of components transported to factories, recycling centers, and end-user nodes are defined as demand, as these node types are collectively referred to as demand nodes throughout the analysis.

Table 5-5 Factory nodes data

Node Number	Node Name	Y- Latitude	X- Longitude	Expected Demand (ton)
52	Acier Lachine Inc	45.476338	-73.543618	235
53	Industries Les Industries Bonimetal Inc	45.620597	-73.538125	235
54	Groupe Canam - Usine	45.608753	-73.416306	235
55	Acier Simmonds	45.429085	-71.827942	235
56	Structures Fabrec Inc	46.813292	-71.30157	235
57	375 Rue de Courcelette	45.410225	-71.89922	235
58	1005 Rue du Père-Daniel	46.349462	-72.501616	235
59	1445 Rue du Grand-Tronc	46.817456	-71.206064	235
60	200 Bd Industriel	45.591283	-73.354634	235

5.3.5 Recycle Center Data

Table 5-6 presents detailed information for the eleven recycling center nodes included in the network. For each node, geographic coordinates (longitude and latitude) are provided, along with a unique identifier corresponding to its representation within the chromosome structure of the optimization model. These facilities receive steel components that cannot be salvaged at reuse hubs or refurbished at factory nodes, representing the final recovery pathway within the RSC before material and component disposal.

The recycling centers were selected based on their proximity to the four major cities considered in this study, as well as their functional specialization. All identified facilities are metal recycling centers equipped with the appropriate infrastructure and technology required to process steel components. Compared to other node types in the network, the identification of recycling centers posed fewer challenges, as such facilities are typically located in or near large urban areas to support industrial and construction related waste streams.

Table 5-6 Recycle center nodes data

Node Number	Node Name	Y- Latitude	X- Longitude	Expected Demand
61	AIM Recyclage Québec	46.889354	-71.056697	47
62	Option-Métal Recyclé Du Québec Coopérative de Solidarité	46.983124	-70.94134	47
63	Bourque Métal Inc.	45.470788	-71.386287	47
64	Aciers Orford Inc (Les)	45.374401	-71.792781	47
65	600 Rue Berge-du-Canal	45.443987	-73.647379	47
66	Lacombe et Giasson Inc.	45.620831	-73.649352	47
67	AIM Recyclage Laval	45.665956	-73.621886	47
68	AIM Recyclage Montréal-Est	45.634036	-73.521292	47
69	AIM-RECYCLING	45.442226	-71.9057	47
70	AIM Recyclage Vanier	46.826292	-71.233505	47
71	AIM Recyclage Trois-Rivières	46.343504	-72.582359	47

5.3.6 End-User Data

The process of selecting end-user nodes was considerably more challenging compared to the identification of recycling center RC_j nodes. As previously explained, end-users were identified from among vacant industrial lands and existing industrial storage facilities that are expected to require maintenance, redevelopment, or replacement within the next 50 years. These locations represent potential sites where reused deconstructed components could be integrated into future construction or renovation projects.

Given that end-users constitute the primary recipients of reusable components within the proposed RSC, the largest proportion of component demand is assigned to this node type. Accordingly, a higher demand percentage is allocated to end-user nodes relative to other demand nodes in the network. Table 5-7 provides detailed information on the selected end-user nodes, including their spatial and functional characteristics.

Table 5-7 End-user nodes data

Node Number	Node Name	Y- Latitude	X-Longitude	Expected Demand
72	1455 Bd Industriel	45.326287	-72.125993	611
73	435 Rue Beaubien O #300	45.532879	-73.609034	611
74	Maisons Laprise - Laval	45.570619	-73.689874	611
75	11645 Av. Philippe-Panneton	45.632891	-73.595152	611
76	5385 Rue Rideau	46.799299	-71.333841	611
77	1655 Rue de Beauharnois O	45.533532	-73.65407	611
78	440 Rue Dumais	46.766663	-71.201342	611
79	3050 Bd Sainte-Anne	46.849559	-71.209958	611
80	5255 Rue Robert-Boyd	45.401416	-71.992488	611
81	375 Rue Lachance	46.802992	-71.289524	611
82	2450 Rue de la Sidbec S	46.337152	-72.582568	611
83	430 Rue Léger	45.401704	-71.974482	611
84	175 Ave Saint-Sacrement	46.807866	-71.26504	611
85	9495 Rue Pascal-Gagnon	45.612433	-73.602748	611
86	85 Rue Morane	45.594554	-73.713703	611
87	3050 Boul Matte # E	45.435214	-73.471102	611
88	420 Rue Dumais	46.766604	-71.204376	611
89	5069 Bd Saint-Jean-Baptiste	45.649315	-73.526466	611
90	3005 Boul Matte #300a	45.434683	-73.469026	611
91	Groupe Canam - Centre administratif	45.568135	-73.413844	611

5.3.7 Hub Data

At the hub level, the capacity of each potential hub location (CA_{H_K}) is defined based on the availability of vacant land and existing infrastructure within the selected industrial areas (see Table 5-2). The estimation of hub capacities follows the floor-area-based industrial land-use assumptions described earlier in Section 5.3.2. As summarized in Table 5-8, the geographic coordinates (longitude and latitude) of each hub are also provided to ensure spatial accuracy in the spatial analysis.

Table 5-8 Hub nodes data

Node Number	Node Name	Y- Latitude	X- Longitude	Capacity (ton)
1	13 Rue Mallory	45.383756	-71.784977	20,000
2	435 Rue Joseph-Latour	45.470685	-71.950721	30,000
3	Industries Fournier Division Construction	46.378774	-72.610285	40,000
4	Westlund Trois-Rivières	46.33233	-72.563593	20,000
5	690 Bd Roland-Godard	45.788878	-74.030299	30,000
6	55 Rte 116 Ouest	45.789431	-72.024648	25,000
7	Quebec Societe-Parc Industriel	46.374926	-72.348207	10,000
8	Parc industriel Armand-Viau	46.828057	-71.320271	35,000
9	1160 Rue de la Concorde	46.734486	-71.204228	30,000
10	3800 Bd de Monseigneur-Fortier	45.431163	-71.936874	40,000
11	YUL5 - Amazon Centre de Tri	45.476705	-73.440504	32,000
12	5555 Rue Ernest-Cormier	45.638248	-73.630704	22,000

The selection of potential hub locations was guided by their proximity to industrial zones and their strategic positioning relative to the four major cities within the study region. The feasibility of locating hubs at intermediate positions between urban centers was also examined to evaluate whether centralized or decentralized configurations would provide more efficient network performance. These locations were therefore chosen to improve network connectivity, facilitate material flows, and minimize overall transportation distances across the reverse supply chain.

5.4 Transportation Network Data

Figure 5-2 illustrates an example of transportation routes within the proposed RSC network for a selected area of the City of Montreal. The vertical bars displayed at each node represent the quantities of components associated with different node types. For deconstruction sites, recycling centers, and factories, the bar heights indicate the estimated loads of components. For hub nodes, as previously illustrated in Figure 5-1(b), the bar height represents the hub capacity (CA_{H_K}).

The transportation paths (blue lines) and the overall network configuration are generated using the Network Analyst extension in ArcGIS, which is capable of solving complex routing problems by identifying optimal paths based on spatial and logistical constraints. This tool enables the estimation of efficient transportation routes within the logistics model.

All routes in the network are connected to H_k, which function as service and decision-making centers. Refurbished components processed at the hubs may be redistributed to U_n or reuse in future construction projects. Depending on the condition of the components, materials may alternatively be transported from the hubs to RC_m or F_l for further processing or advanced refurbishment.

Figure 5-2 The paths in the RSC network in a part of Montreal city

As indicated in the map legend of Figure 5-2, the scale of the bars is standardized, where bars of equal height correspond to 5,000 tons of material. For recycling centers and factories, the bar heights represent the approximate quantities of materials transported from hubs based on component condition. For deconstruction sites, the bars indicate the quantities of components extracted and transported to hubs. For hub nodes, the bars represent storage capacity, while for end-user nodes, they illustrate the estimated future demand for reusable components in new construction projects.

5.5 Optimization Results

Following the implementation of the optimization model described in Chapter 3, the MATLAB-based genetic algorithm was executed for more than 1,000 iterations. After a total of 120,100 function evaluations (NFE), the algorithm converged to an optimal solution, which is illustrated in Figure 5-3. The NFE represents the cumulative number of fitness function evaluations used to assess the quality of candidate solutions throughout the optimization process, including evaluations performed during population initialization, crossover, mutation, and overall population assessment.

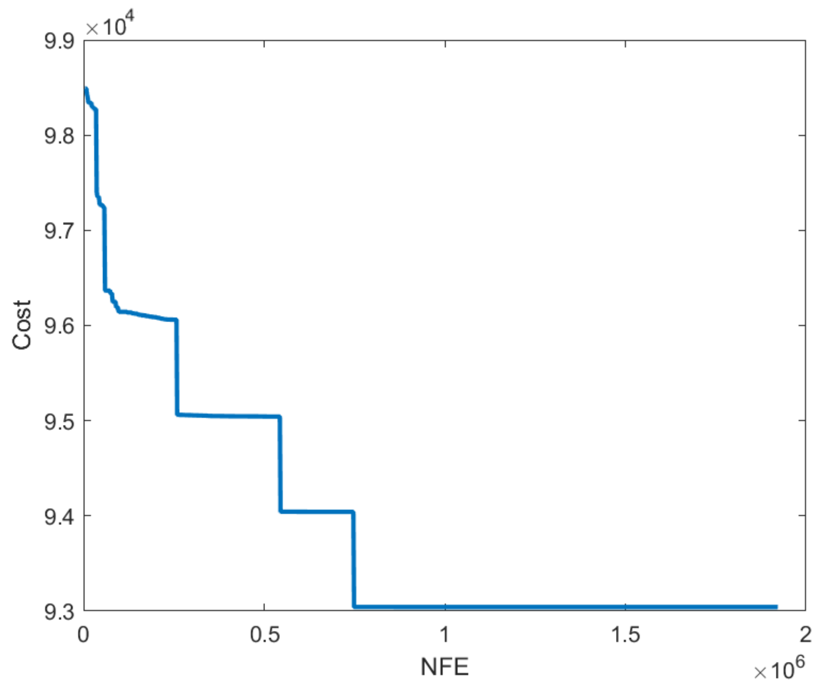


Figure 5-3 Diagram of cost (CA$) based on NFE count

Upon completion of the optimization, six hub locations were selected from the twelve potential candidates, as summarized in Table 5-9. The frequency values reported in the table indicate the number of nodes assigned to each selected hub, as defined in Chapter 3. These frequencies reflect the relative importance and strategic significance of each hub within the network, based on its ability to efficiently serve surrounding nodes across the four major cities.

In addition, Figure 5-4 from MATLAB, shows how this allocation happened among the hubs. Each bar represents a hub, and the stacked segments show the number of demand node of each type assigned to that hub by the GA.

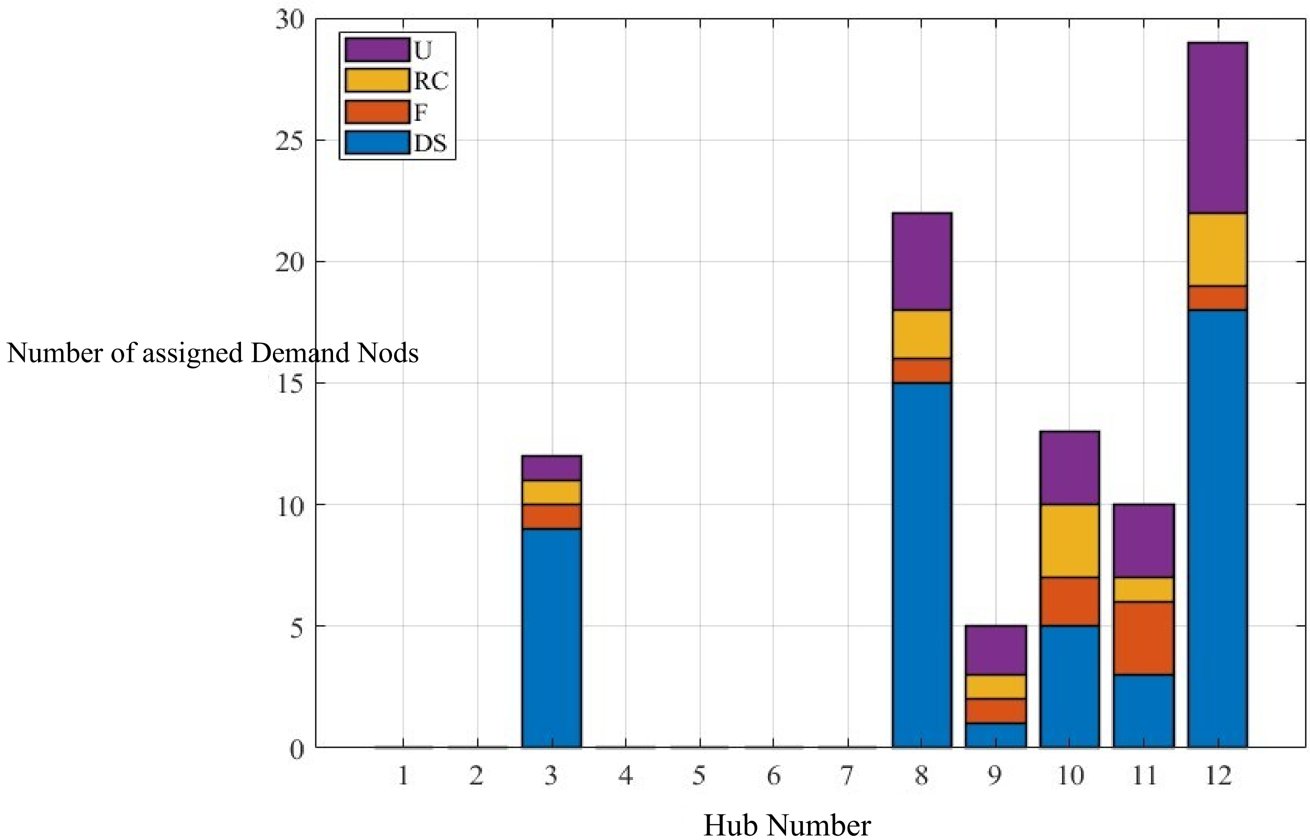


Figure 5-4 Allocation of hubs to demand nodes

Table 5-10 presents the selected hubs ranked according to their priority (as shown in Table 5-9), along with the corresponding nodes allocated to each hub, including DS, F, RC, and U. The table lists the assigned demand nodes using their respective index numbers, which are directly extracted from the optimal chromosome obtained through the optimization process.

Table 5-10 indicate that two hubs were allocated to each city of Montreal and Quebec City. H_{12} and H_{11} for Montreal and H_8 and H_9 are allocated for Quebec City. While H_3 services Trois-Rivières and H_{10} is located at Sherbrooke.

This outcome can be attributed to their substantially higher demand levels, driven by anticipated new construction projects, as well as their logistical feasibility within the network. In contrast, one hub was selected for each of Sherbrooke and Trois-Rivières, reflecting comparatively lower demand and a more limited spatial influence within the network.

Notably, the capacities of the hubs located in Montreal and Quebec City are relatively lower than those in Sherbrooke and Trois-Rivières. This difference is primarily due to higher population densities and limited land availability in Montreal and Quebec City, which constrain the size of potential hub facilities. In contrast, the latter cities offer greater land availability, allowing for larger capacity hubs.

After the hub locations are selected and all demand nodes are allocated to the chosen hubs, the actual capacity required for each hub to operate effectively and service all assigned nodes can be calculated. Table 5-9 presents both the required capacity and the assumed capacity (CA_{H_K}) for each selected hub. Comparing these two values provides valuable insights for optimizing initial capital investment and logistical planning, as it enables the identification of potential overcapacity or under-capacity at specific locations. This comparison supports more informed decision-making regarding hub sizing and location selection, thereby improving the overall efficiency and cost effectiveness of the proposed network.

Table 5-9 The chosen hubs and their ranks

Hub Index Number	Rank	Frequency	Assumed Capacity (1000 ton)	Required Capacity (1000 ton)
1	0	0	20	0
2	0	0	30	0
3	4	12	40	12.5
4	0	0	20	0
5	0	0	30	0
6	0	0	25	0
7	0	0	10	0
8	2	22	35	11.4
9	6	5	30	2.6
10	3	13	40	7.6
11	5	10	32	2.3
12	1	29	22	21.8

Table 5-10 Allocated nodes to each chosen hub

Hub Number	Allocated Node Index			
H	***DS***	***F***	***RC***	***U***
12	32,33,34,35,36,37,38,39,40,41,42,43, 44,45,46,47,48,51	53	66,67,68	73,74,75,77,85, 86,89
8	16,17,18,19,20,21,22,23,24,26,27,28, 29, 30,31	59	62,70	76,79,81,84
10	11,12,13,14,15	55,57	63,64,69	72,80,83
3	2,3,4,5,6,7,8,9,10	58	71	82
11	1,49,50	52,54,60	65	87,90,91
9	25	56	61	78,88

Figure 5-5 presents a GIS-based visualization of the spatial allocation of customers to servers obtained from the GA. The figure integrates geographic information with the optimization results by displaying the exact locations of all servers and customer nodes, along with the assignment relationships between them.

In this figure, hub locations (k_1–k_{12}) are explicitly annotated to allow direct identification of each facility. Different symbols are used to distinguish customer types, including deconstruction sites (DS), factories (F), recycling centers (RC), and end-users (U). Straight-line connections between customer nodes and hubs represent the allocation decisions determined by the GA in the final solution.

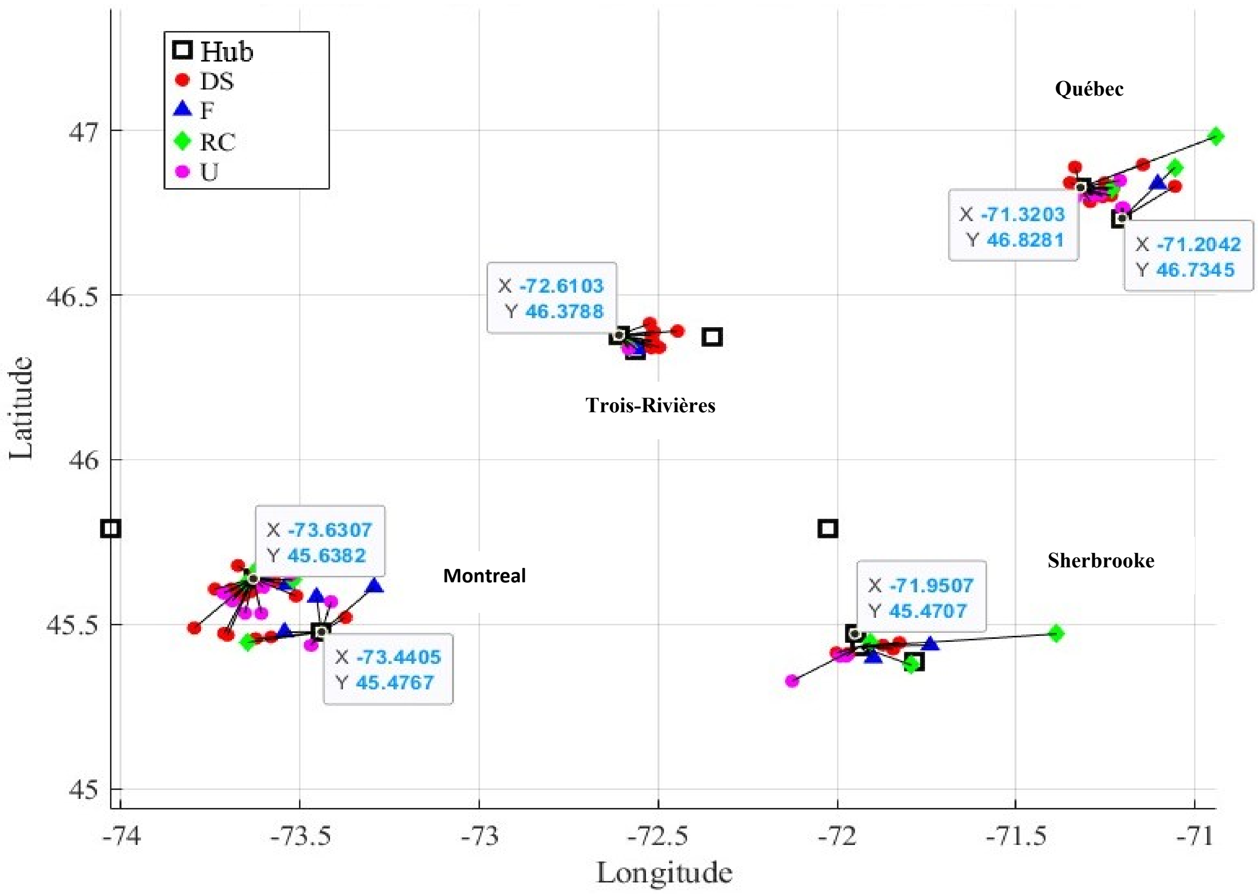


Figure 5-5 GIS- Style allocation map

The figure provides a spatial interpretation of the optimization results by illustrating how customer nodes are clustered around selected hubs. The presence of dense connection patterns around specific hubs indicates their role as active facilities, while the absence of connections for other hubs highlights inactive locations, thereby visually confirming compliance with the maximum server constraint H_{max}.

Moreover, the length and direction of the assignment lines offer qualitative insight into the trade-off between transportation distance and demand node satisfaction embedded in the objective function. For instance, in the two big cities of this study, Montreal Figure 5-6 and Quebec City Figure 5-7, these lengths are more noticeable. Shorter connections indicate geographically efficient allocations, whereas longer links reflect cases where capacity limitations or the global optimization objective require assignments beyond the nearest hub.

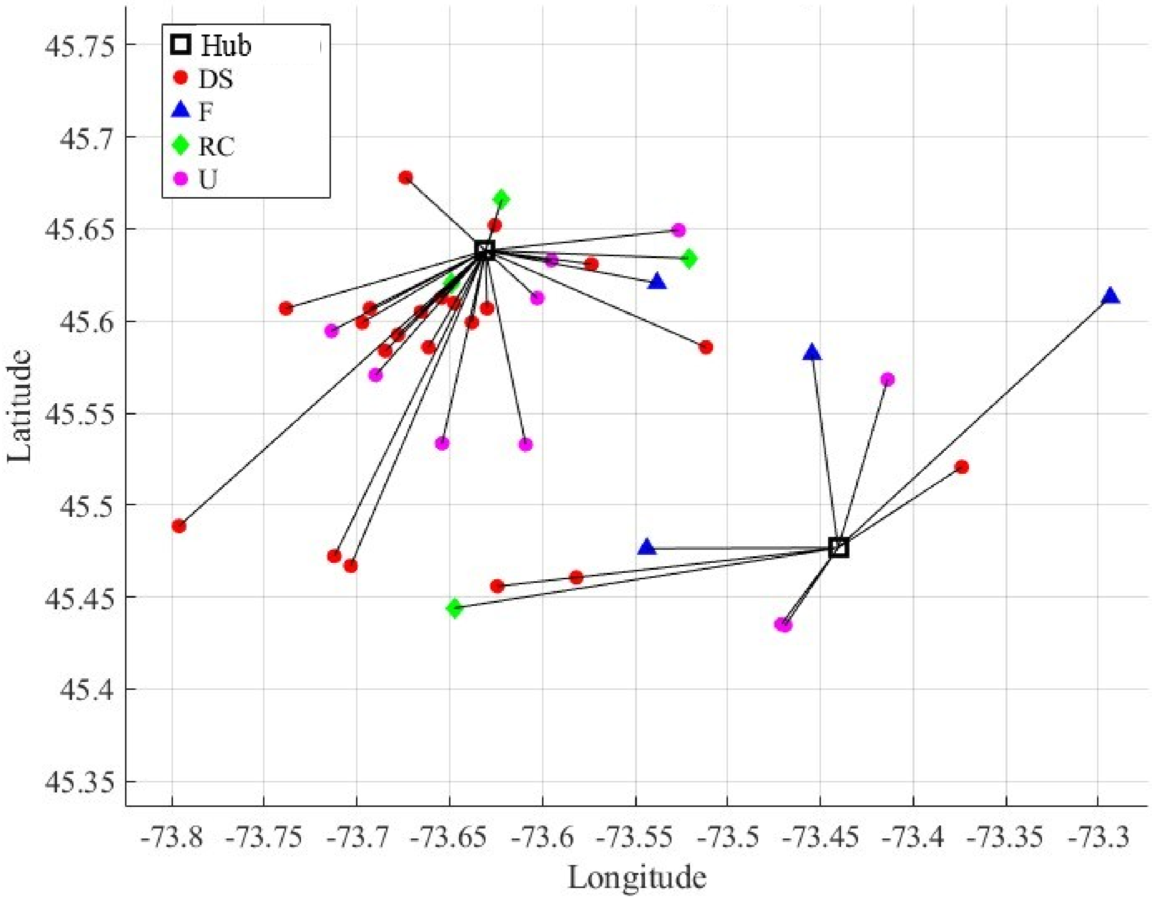


Figure 5-6 GIS-Style allocation map in Montreal

For instance, in the Sherbrooke area Figure 5-8, one of the recycling center connections extends beyond the city boundary. This occurs because the capacities of closer recycling centers have already been reached, requiring the model to allocate the flow to a more distant facility in order to maintain overall system feasibility and optimize the network performance.

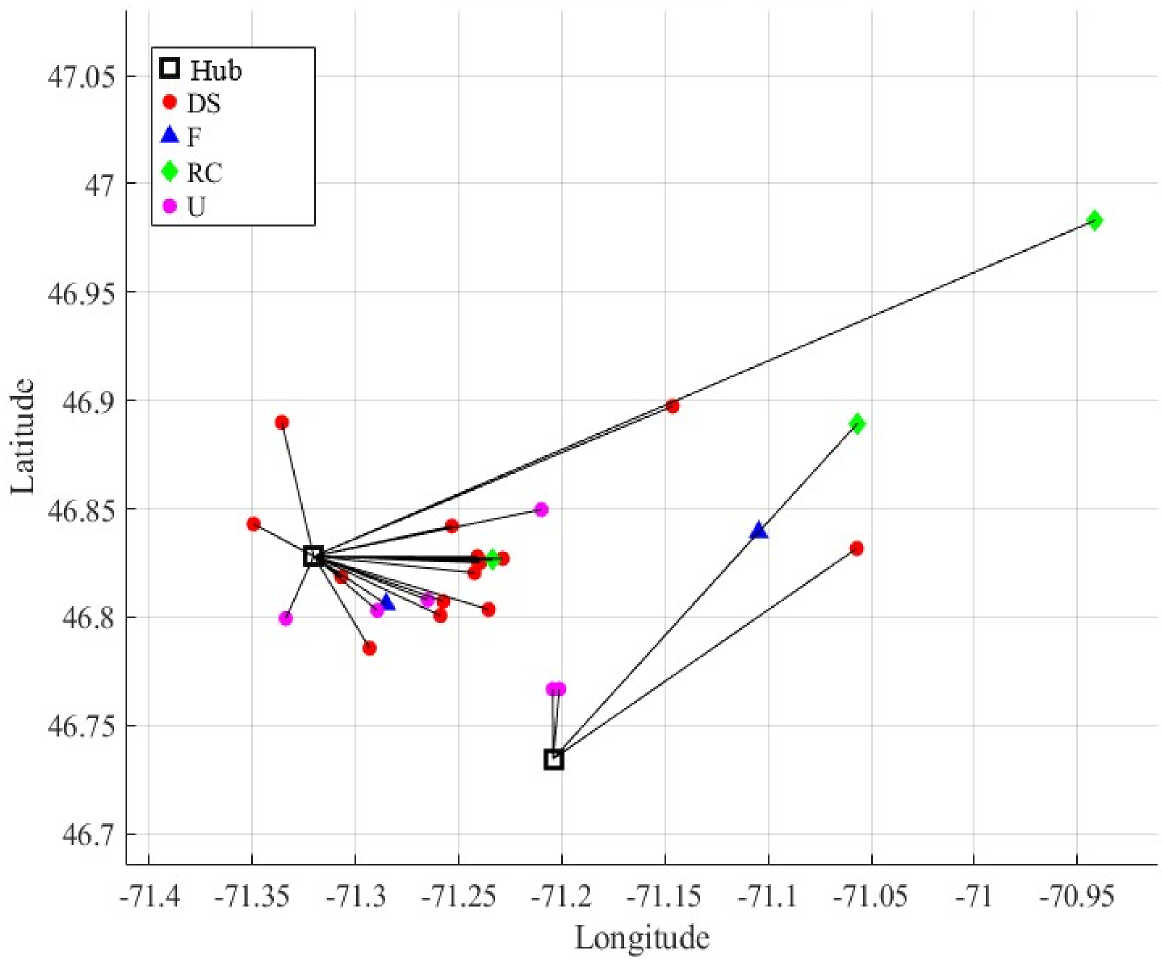


Figure 5-7 GIS-Style allocation map in Quebec City

Figure 5-9 illustrates the spatial distribution of potential hub locations within the Trois-Rivières case study, specifically highlighting two candidate sites that were ultimately not selected by the optimization model. Although these locations may appear geographically superior due to their proximity to demand nodes, they were excluded from the final network configuration due to capacity limitations. This emphasizes a core constraint of the proposed model: the selection process prioritizes operational throughput and functional viability over network distance.

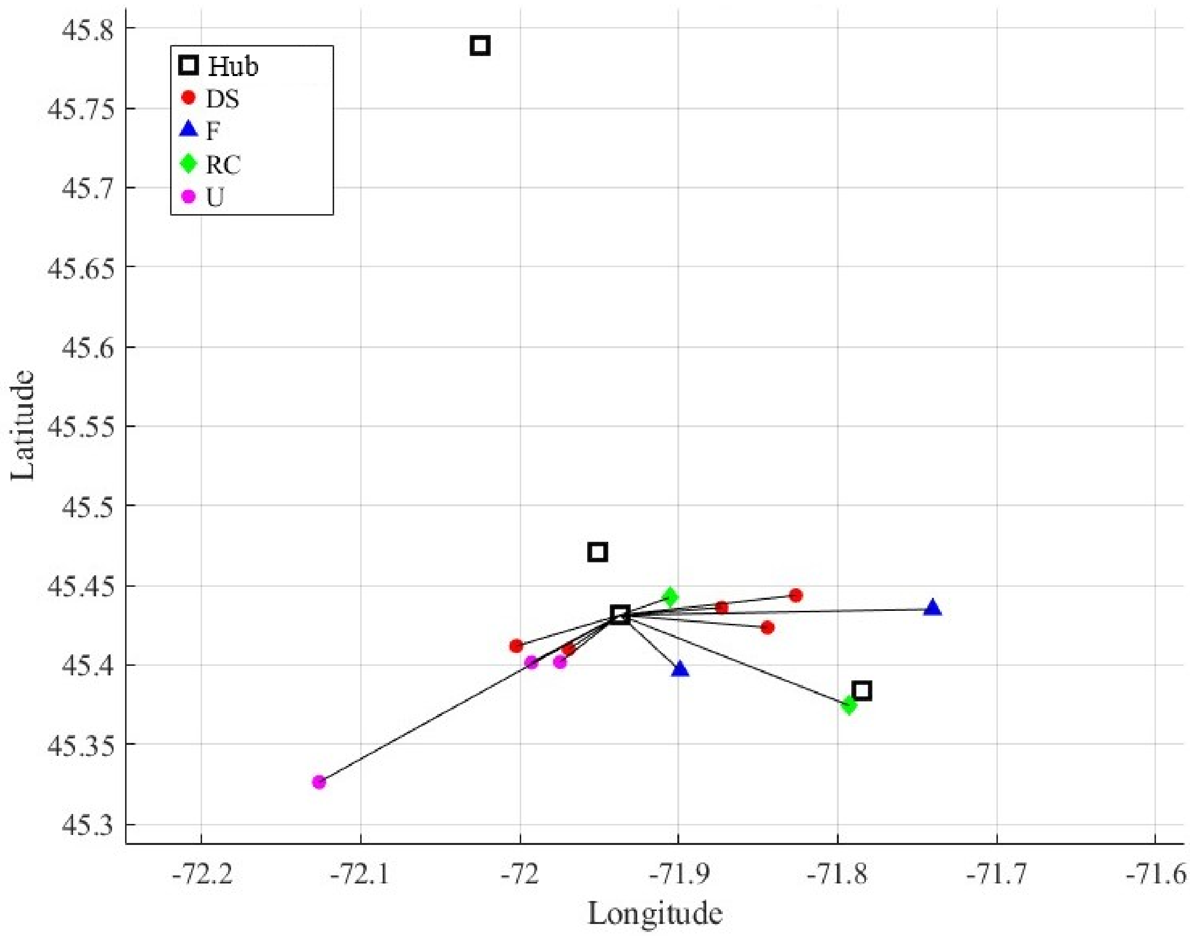


Figure 5-8 GIS-Style allocation map in Sherbrooke

Also, the figure shows the GIS calculation of actual road-trip distances rather than idealized point-to-point measurements made. By utilizing real-world routing data, the model accounts for infrastructure constraints and logistical bottlenecks, ensuring that the identified hub locations are not only theoretically optimal but also practically feasible within the existing regional transport network.

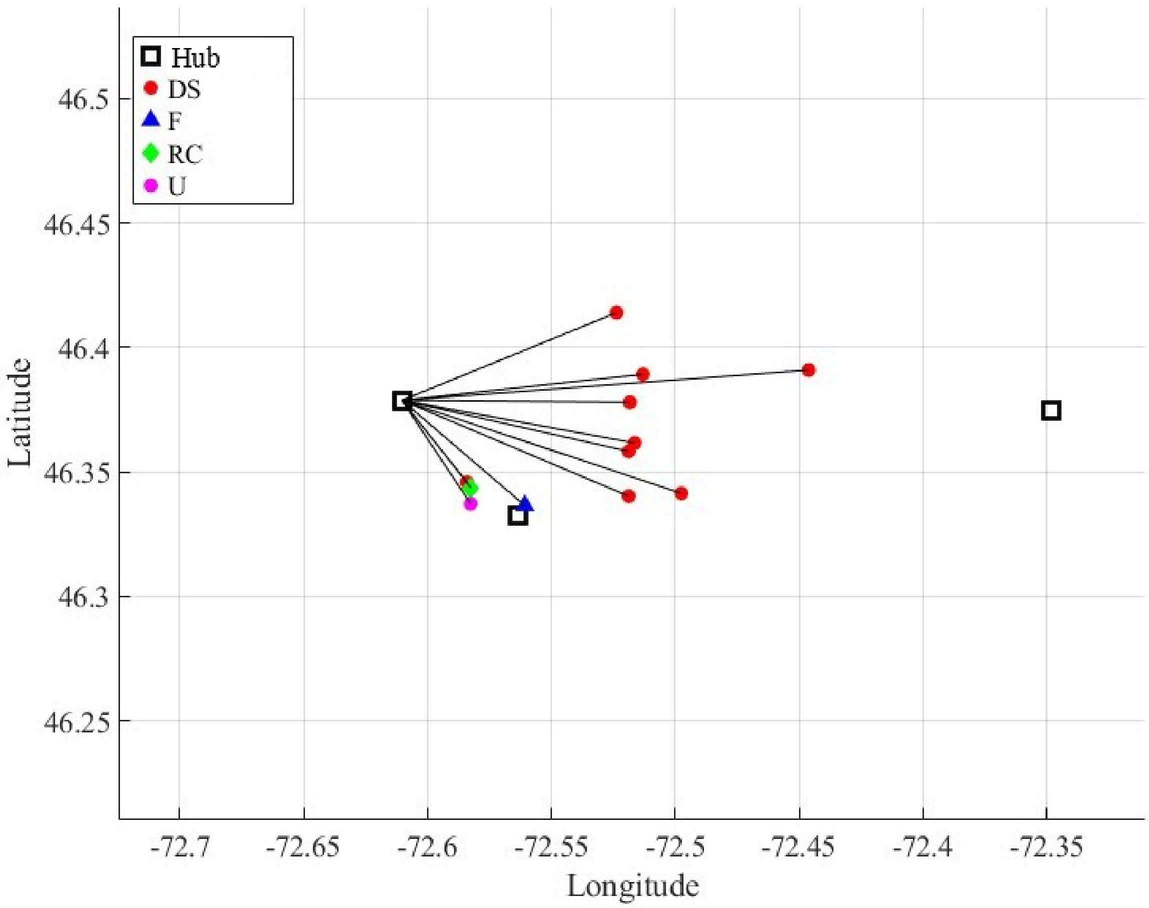


Figure 5-9 GIS-Style allocation map in Trois-Rivières

Figure 5-10 illustrates the evolution of demand node allocation to hubs over the course of the GA iterations. The horizontal axis represents the iteration number, while the vertical axis corresponds to the available hubs (H_1–H_{12}). The color intensity indicates the total aggregated demand node assigned to each server in the best solution identified at each iteration.

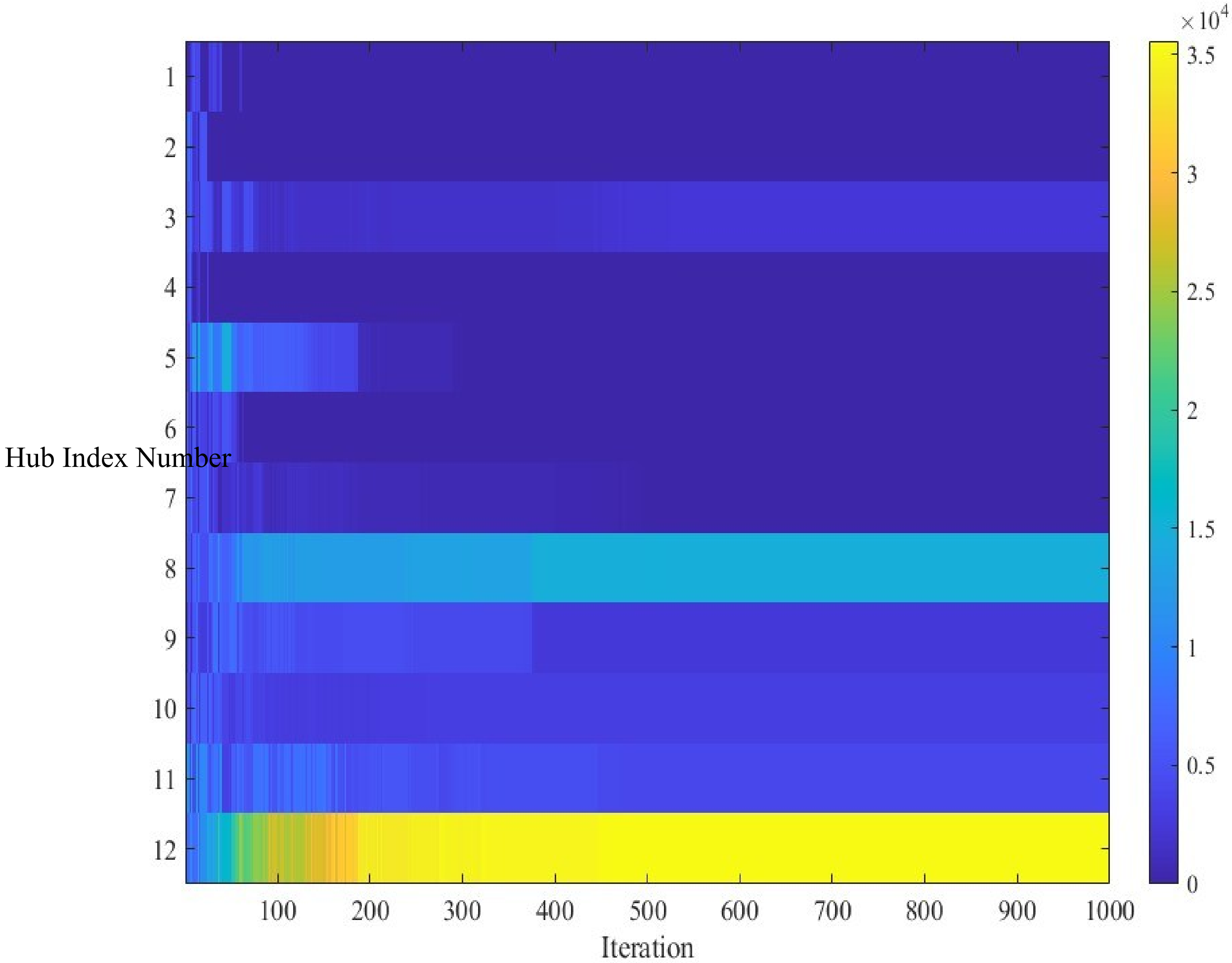


Figure 5-10 Evolution of hub allocation to demand nodes over iterations

This figure provides insight into the dynamic behavior of the decision variables during the optimization process. In the early iterations, the allocation pattern exhibits significant variability, reflecting the exploratory nature of the GA. During this phase, demand node is frequently redistributed among different hubs as the algorithm searches the solution space and evaluates alternative configurations. As the algorithm progresses, the allocation patterns gradually stabilize. Distinct bands of consistent color intensity emerge, indicating that the GA converges toward a stable set of selected hubs. The figure also clearly demonstrates compliance with the maximum hub constraint, as the number of hubs carrying non-zero demand node does not exceed the predefined limit H_{max}.

Moreover, the stabilization of demand node distribution across iterations confirms that the convergence of the objective function is accompanied by structural convergence in the allocation decisions.

Chapter 6. Conclusions and Future Work

6.1 Introduction

This chapter synthesizes the findings of this research, which proposed an integrated framework for optimizing the RSC for recovered steel components. By coupling GIS with an NSGA-II optimization model, a spatial decision-support approach was developed to identify optimal hub locations and component flows. Validated through a case study of four major cities in Québec Province, Montreal, Quebec City, Sherbrooke, and Trois-Rivieres, the results demonstrate that strategic planning significantly improves logistical efficiency and supports the practical implementation of CE principles.

6.2 Summary of Research

This study addressed the problem of designing an efficient RSC for reusable steel components recovered from deconstructed buildings. The research focused on identifying optimal hub locations and facility allocation strategies that minimize transportation costs while ensuring that processing and redistribution capacities are respected.

The first stage of the research involved the development of a conceptual RSC framework that represents the potential flows of components within the deconstruction ecosystem. The framework includes several key node types: deconstruction sites, factories, recycling centers, end-users, and hubs. Deconstruction sites represent buildings that are expected to reach the end of their service life and generate recoverable structural steel components. Factories serve as facilities where reusable components may undergo major processing or refurbishment before being integrated into new construction projects. Recycling centers process components that cannot be repaired or directly reused as components and would be used as materials. End-users represent potential destinations for reclaimed steel components in future building developments.

A key feature of the proposed framework is the introduction of repairing hub facilities. These hubs serve as operational nodes where components can be temporarily stored, inspected, repaired, adjusted, and redistributed to the end-users within the supply chain. By consolidating component flows at strategically located hubs, the network can improve logistical coordination and reduce transportation inefficiencies.

Following the development of the conceptual framework, a hypothetical case study is developed based on a sample spatial dataset constructed using GIS tools. Geographic information related to industrial facilities, recycling centers, building permits, and land availability was collected and processed to identify relevant nodes within the study region. In total, 91 functional nodes were incorporated into the model, including 51 deconstruction sites, 9 factories, 11 recycling centers, and 20 end-user nodes. Additionally, 12 potential hub locations were identified based on the availability of vacant industrial land parcels with sufficient area to accommodate logistics operations.

The spatial dataset was then integrated into a mathematical optimization model designed to determine the optimal configuration of the RSC network. GA (NSGA II) was implemented in MATLAB to solve the hub location optimization problem, as the complexity of the network and the combinatorial nature of the decision variables made traditional exact optimization approaches computationally challenging. The GA approach allowed the model to explore a large solution space and iteratively converge toward near-optimal configurations.

The objective function of the optimization model was defined to minimize overall transportation costs across the network while satisfying capacity constraints for hubs and ensuring feasible component flows between nodes. The model considered distances between all nodes, estimated quantities of recoverable steel components, and processing capacities associated with potential hub facilities.

The optimization process involved more than 120,000 function evaluations before reaching convergence. The results indicated that six hubs were selected from the twelve candidate locations, forming a network configuration capable of efficiently connecting deconstruction sites with factories, recycling centers, and end-user destinations. The resulting hub network demonstrated improved transportation efficiency by reducing overall travel distances while maintaining balanced component distribution across the RSC.

Visualization of the optimized network further illustrated how nodes were assigned to hubs according to proximity, capacity constraints, and the overall objective function. In most cases, nodes were connected to nearby hubs, resulting in relatively short transportation distances. However, some longer connections were observed in situations where nearby hub capacities were already reached, requiring the model to allocate nodes to more distant hubs in order to maintain feasibility within the network.

6.3 Research Contributions

The findings of this research contribute to the growing body of knowledge on circular construction logistics and RSC design in several important ways.

First, the study demonstrates the effectiveness of integrating GIS-based spatial analysis with evolutionary optimization algorithms to solve complex logistics planning problems. By utilizing GIS, real geographic data and spatial relationships are incorporated directly into the model, ensuring that optimization results reflect realistic transportation routes and regional infrastructure constraints. Simultaneously, GA provides a flexible and robust method for exploring large solution spaces and identifying efficient hub configurations.

Second, the research highlights the importance of repairing hubs as critical infrastructure elements within the construction RSC. The introduction of these hub facilities enables the consolidation and redistribution of recovered components, significantly improving coordination between deconstruction activities and future construction demands. These hubs provide the necessary operational space for inspection, repair, and storage, essential steps in ensuring that recovered components meet the rigorous requirements of new building projects.

Third, building upon this logistical and operational foundation, the study proposes a structured RSC framework, as shown in Figure 3-1, specifically tailored to the reuse of structural steel components. While many existing studies focus primarily on traditional recycling, this research emphasizes higher-value recovery pathways, including inspection, refurbishment, and direct component reuse. By prioritizing these strategies, the proposed framework ensures greater value retention and contributes to more sustainable resource management practices within the construction sector.

Additionally, this research contributes a practical application of the proposed framework through a real-world case study in Québec. By utilizing actual geographic and infrastructure data, the study demonstrates the real-world implementation of optimization-based RSC planning, showing that strategic hub placement significantly improves the efficiency of redistribution networks and enhances the economic viability of reuse initiatives. Furthermore, the visualization of optimized component flows provides critical insights into supply chain behavior under varying capacity and distance constraints. These findings offer a robust evidence base for policymakers, urban planners, and construction stakeholders to make informed decisions regarding infrastructure investments and CE strategies.

6.4 Limitations and Future Work

While the methodology is validated through the case study, several limitations regarding the scope and data environment of this study should be acknowledged.

- **Reusable Component Assumptions:** One limitation relates to the assumptions made regarding the condition and reuse potential of recovered components. In the current model, the allocation of components between refurbishment facilities, recycling centers, and end users is based on estimated percentages derived from existing literature. In reality, the condition of deconstructed components can vary significantly depending on building age, structural design, maintenance history, and dismantling practices. Future studies could incorporate detailed inspection data or structural assessment models to more accurately determine the reuse potential of individual components.
- **Spatial Data Precision:** Another limitation relates to the availability and accuracy of spatial data used to define the locations of supply chain nodes. In this study, the geographic positions of deconstruction sites and end-user nodes were estimated based on available datasets, building permit records, and spatial analysis conducted in the GIS platform. Although these approximations provide a reasonable representation of potential component sources and demand points, the use of more precise and comprehensive datasets could

further improve the reliability of the optimization results. For instance, access to detailed information regarding the exact locations, schedules, and characteristics of future deconstruction projects, as well as confirmed locations of end-users interested in reclaimed components, would allow the model to better represent real supply and demand conditions. Incorporating such high-resolution spatial data would enhance the accuracy of transportation distance calculations, improve node allocation decisions, and ultimately increase the efficiency and practical applicability of the optimized RSC network.

- **Dynamic Flow period:** Another limitation concerns the static nature of the optimization model. The present study considers a fixed network configuration and a single planning horizon. However, construction component flows evolve over time as buildings are deconstructed and new construction projects emerge. Future research could extend the model to incorporate dynamic or multi-period optimization approaches using time series analysis, that account for temporal variations in supply and demand.
- **Economic Scope:** The model could also be improved by incorporating additional cost factors beyond transportation distances. For example, operational costs associated with hub facilities, labor requirements for component refurbishment, and storage costs could be included to provide a more comprehensive economic evaluation of the RSC.
- **Hub Diversity:** Furthermore, the current study focuses primarily on steel components. While steel is an important structural component with high reuse potential, many other building components, such as concrete, timber, and facade elements, also represent significant opportunities for circular reuse. Future research could expand the framework to accommodate multi-component RSCs, allowing different component streams to be processed through specialized hubs or facilities.
- **Component Tracking:** Another promising direction for future research involves the integration of digital construction technologies such as BIM, material passports, and digital product passports. These tools can provide detailed information about building components, including their material composition, structural properties, and service history. Integrating such data into RSC models could greatly enhance traceability and enable more precise planning of component recovery operations.

Finally, future work could incorporate environmental performance indicators into the optimization framework. In addition to minimizing transportation costs, the model could be extended to evaluate embodied carbon emissions, energy consumption, and lifecycle environmental impacts associated with different supply chain configurations. Such multi-objective optimization approaches would allow decision-makers to balance economic efficiency with environmental sustainability, further supporting the transition toward low-carbon circular construction systems.

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Appendices

Appendix A. The MATLAB Code of Optimization and GA Algorithm.

The following section provides the MATLAB source code for the GA developed to optimize the RSC model. The algorithm processes real-world spatial and logistical data to determine the most cost-efficient network configuration.

Key inputs integrated within this script include:

- Node Spatiality: Longitudinal and latitudinal coordinates for all five primary node categories.
- Operational Constraints: Throughput capacity for candidate hub locations.
- Material Loads: Tonnages of steel extracted from deconstruction sites based on building area calculations.
- Demand Allocation: Component flow volumes directed to each node based on modeled demand requirements.

Environment:

```
%% Problem Definition

global NFE;
NFE = 0;

% Define the number of customers for each type
nDS = 51; % Number of Deconstruction Sites
nF = 9; % Number of Factories
nRC = 11; % Number of Recycle Centers
nU = 20; % Number of End Users
A = nDS + nF + nRC + nU; % Total number of customers
K = 12; % Number of servers

% Input data for customer locations
lonDS = [-73.37378141, -72.51828, -72.497511, -72.518742, -72.518742, -72.584067, -
72.516292, -72.446068, -72.523641, -72.513026, -71.84406, -71.826207, -71.872899, -
71.969029, -72.001988, -71.241013, -71.239639, -71.241013, -71.228653, -71.257492, -
71.235519, -71.242386, -71.239639, -71.258865, -71.056992, -71.253372, -71.146256, -
71.33577, -71.349503, -71.306931, -71.293198, -73.625661, -73.673726, -73.573475, -
73.661366, -73.677846, -73.62978, -73.697072, -73.6545, -73.692952, -73.63802, -
73.647633, -73.665486, -73.73827, -73.684712, -73.712178, -73.511677, -73.795949, -
73.581715, -73.624287, -73.7034]; % Longitude of Deconstruction Sites
latDS = [45.52069024, 46.377985, 46.341355, 46.340228, 46.358264, 46.345865,
46.361645, 46.39094, 46.414027, 46.38925, 45.423339, 45.443576, 45.435868, 45.409843,
45.411771, 46.827863, 46.825044, 46.825983, 46.826923, 46.807188, 46.803428,
46.820345, 46.825983, 46.800607, 46.831621, 46.841955, 46.897348, 46.88984,
46.842894, 46.818466, 46.785564, 45.652009, 45.677921, 45.630886, 45.585733,
45.59246, 45.606873, 45.599186, 45.612637, 45.606873, 45.599186, 45.609755,
45.604951, 45.606873, 45.583811, 45.47221, 45.585733, 45.488579, 45.460653,
45.455836, 45.466992]; % Latitude of Deconstruction Sites

lonF = [-73.543618, -73.538125, -73.293679, -71.740173, -71.10458, -71.899041, -
72.56073, -71.2852, -73.454541]; % Longitude of Factories
```

```
latF = [45.476338, 45.620597, 45.612912, 45.434867, 46.839189, 45.39629, 46.336486,
46.805884, 45.582092]; % Latitude of Factories

lonRC = [-71.056697, -70.94134, -71.386287, -71.792781, -73.647379, -73.649352, -
73.621886, -73.521292, -71.9057, -71.233505, -72.582359]; % Longitude of Recycle
Centers
latRC = [46.889354, 46.983124, 45.470788, 45.374401, 45.443987, 45.620831, 45.665956,
45.634036, 45.442226, 46.826292, 46.343504]; % Latitude of Recycle Centers

lonU = [-72.125993, -73.609034, -73.689874, -73.595152, -71.333841, -73.65407, -
71.201342, -71.209958, -71.992488, -71.289524, -72.582568, -71.974482, -71.26504, -
73.602748, -73.713703, -73.471102, -71.204376, -73.526466, -73.469026, -73.413844]; %
Longitude of End Users
latU = [45.326287, 45.532879, 45.570619, 45.632891, 46.799299, 45.533532, 46.766663,
46.849559, 45.401416, 46.802992, 46.337152, 45.401704, 46.807866, 45.612433,
45.594554, 45.435214, 46.766604, 45.649315, 45.434683, 45.568135]; % Latitude of End
Users

% Combine all locations into a single array
lonC = [lonDS, lonF, lonRC, lonU];
latC = [latDS, latF, latRC, latU];

% Input data for demands
dDS = [763.434, 178.343, 145.746, 221.6065, 440.3685, 130.748, 122.4845, 146.2415,
69.1105, 83.1585, 79.4665, 204.29928, 119.07378, 177.9975, 136.026, 155.74626,
887.82102, 191.26692, 115.39962, 661.284, 552.15, 1493.1, 261.63108, 774.36, 1134,
769.72302, 1064.934, 169.236, 2966.49648, 1000.728, 1005.21, 478.224, 888.4836,
1165.32, 421.848, 1227.798, 546.048, 3257.57592, 1366.2, 996.84, 1502.3394, 405,
577.8, 2932.2, 2890.35, 3261.276, 2371.0077, 2831.8086, 541.21662, 262.47618,
3788.208];   % Demands for Deconstruction Sites
dF = [235, 235, 235, 235, 235, 235, 235, 235, 235]; % Demands for Factories
dRC = [47, 47, 47, 47, 47, 47, 47, 47, 47, 47, 47]; % Demands for Recycle Centers
dU = [611, 611, 611, 611, 611, 611, 611, 611, 611, 611, 611, 611, 611, 611, 611, 611,
611, 611, 611, 611]; % Demands for End Users

% Combine all demands into a single array
d = [dDS, dF, dRC, dU];

% Input data for server locations
lonS = [-71.784977, -71.950721, -72.610285, -72.563593, -74.030299, -72.024648, -
72.348207, -71.320271, -71.204228, -71.936874, -73.440504, -73.630704]; % Longitude
of servers
latS = [45.383756, 45.470685, 46.378774, 46.33233, 45.788878, 45.789431, 46.374926,
46.828057, 46.734486, 45.431163, 45.476705, 45.638248]; % Latitude of servers

% Input data for server capacities
capacity = [20,000, 30,000, 40,000, 20,000, 30,000, 25,000, 10,000, 35,000, 30,000,
40,000, 32,000, 22,000]; % Capacity of each server

% Define the maximum number of servers that can be built
Hmax = 4; % Maximum number of servers to be chosen

% Radius of the Earth in kilometers
R = 6371;
```

```
% Calculate distances between each customer and server using Haversine Formula
distance = zeros(A, K);

for i = 1:A
    for j = 1:K
        % Convert degrees to radians
        lonC_rad = deg2rad(lonC(i));
        latC_rad = deg2rad(latC(i));
        lonS_rad = deg2rad(lonS(j));
        latS_rad = deg2rad(latS(j));

        % Haversine formula
        delta_lat = latS_rad - latC_rad;
        delta_lon = lonS_rad - lonC_rad;
        a = sin(delta_lat / 2)^2 + cos(latC_rad) * cos(latS_rad) * sin(delta_lon /
2)^2;
        c = 2 * atan2(sqrt(a), sqrt(1 - a));
        distance(i, j) = R * c; % Distance in kilometers
    end
end


nVar = A; % Number of Decision Variables (assignments of customers)
VarSize = [1, nVar]; % Decision variables matrix size


%% GA Parameters
MaxIt = 1000; % Max number of iterations
nPop = 2000; % Population size
pc = 0.95;        % Crossover percentage
nc = 2 * round(pc * nPop / 2);  % Number of offspring (parents)
pm = 0.01;        % Mutation percentage
nm = round(pm * nPop);          % Number of mutants


% MaxIt = 1; % Max number of iterations
% nPop = 2; % Population size
% pc = 0.8;        % Crossover percentage
% nc = 2 * round(pc * nPop / 2);  % Number of offspring (parents)
% pm = 0.3;        % Mutation percentage
% nm = round(pm * nPop);          % Number of mutants

% %% Initialization
empty_individual.Position = [];
empty_individual.Cost = [];

pop = repmat(empty_individual, nPop, 1);

for i = 1:nPop
% for i = 1:1
    % Initialize Position
    pop(i).Position = InitializeValidChromosome(A, K);
    % Evaluation
    pop(i).Cost = CalculateCost(pop(i).Position,capacity, d, distance, Hmax);
end
```

```
% Sort Population
Costs = [pop.Cost];
[Costs, SortedOrder] = sort(Costs);
pop = pop(SortedOrder);


% Store Best Solution
BestSol = pop(1);

% Array to Hold Best Cost Values
BestCost = zeros(MaxIt, 1);

% Array to Hold Number of Function Evaluations
nfe = zeros(MaxIt, 1);

% Store best chromosome at each iteration (for evolution plots)
BestPosHistory = zeros(MaxIt, A);

%% Main Loop
for it = 1:MaxIt
    % Crossover
    popc = repmat(empty_individual, nc / 2, 2);
    for k = 1:nc / 2
        % Select First Parent Randomly
        i1 = randi([1, nPop]);
        P1 = pop(i1);
        % Select Second Parent
        i2 = randi([1, nPop]);
        P2 = pop(i2);

        % Apply Crossover
        [popc(k, 1).Position, popc(k, 2).Position] =
SinglePointCrossover(P1.Position, P2.Position);

        % Evaluate Offsprings
        popc(k, 1).Cost = CalculateCost(popc(k, 1).Position, capacity, d, distance,
Hmax);
        popc(k, 2).Cost = CalculateCost(popc(k, 2).Position, capacity, d, distance,
Hmax);
    end
    popc = popc(:);   % To make it only one column

    % Mutation
    popm = repmat(empty_individual, nm, 1);
    for k = 1:nm

        % Select Parent
        i = randi([1, nPop]);
        p = pop(i);
        % Apply Mutation
        popm(k).Position = MutateValidChromosome(p.Position, K, Hmax);

        % Evaluate Mutant
```

```
        popm(k).Cost = CalculateCost(popm(k).Position, capacity, d, distance, Hmax);

    end

    % Create Merged Population
    pop = [pop; popc; popm];

    % Sort Population
    Costs = [pop.Cost];
    [Costs, SortedOrder] = sort(Costs);
    pop = pop(SortedOrder);

    % Truncation
    pop = pop(1:nPop);

    % Store Best Solution Ever Found
    BestSol = pop(1);
% Save best allocation for this iteration
    BestPosHistory(it,:) = BestSol.Position;

    % Store Best Cost Ever Found
    BestCost(it) = BestSol.Cost;

    % Store NFE
    nfe(it) = NFE;

    % Show Iteration Information
    disp(['Iteration ' num2str(it) ': NFE=' num2str(nfe(it)) ', Best Cost = '
num2str(BestCost(it))]);
    disp(['Best Chromosome: ' num2str(BestSol.Position)]);
    [r, f, v] = ordernrank(BestSol.Position);
    table(r, f, v, 'VariableNames', {'Rank', 'Occurrence', 'Value'})
    disp(v(1:Hmax,1).')
end

%% Results
figure;
plot(nfe, BestCost, 'LineWidth', 2);
xlabel('NFE');
ylabel('Cost');

%% Supporting Functions

function [z] = CalculateCost(x,hosna_cap, hosna_demand, hosna_distance, hosna_Hmax)
    % x: Vector of customer assignments to servers
    % distance: [A x K] matrix of distances between each customer and server
    % demand: [1 x A] vector of demands for each customer
    % capacity: [1 x K] vector of server capacities
    % Hmax: Maximum number of servers that can be chosen

    global NFE;
    if isempty(NFE)
        NFE = 0;
    end
    NFE = NFE + 1;
```

```
    % Initialize the total cost
    total_cost = 0;

    % Server usage tracker
    server_usage = zeros(1, length(hosna_cap));

    % Demand tracker per server
    server_demand = zeros(1, length(hosna_cap));

    % Assign customers to servers and calculate cost

    for i = 1:length(hosna_demand)
        server = x(i);
        server_demand(server) = server_demand(server) + hosna_demand(i);


        % Check capacity constraint
        if server_demand(server) > hosna_cap(server)
            total_cost = total_cost + 1e6; % Penalize infeasible solutions
        end

        server_usage(server) = server_usage(server) + 1;
        total_cost = total_cost + hosna_distance(i, server) * hosna_demand(i) *
0.0742;
    end

    % Check maximum server constraint
    active_servers = find(server_usage > 0);
    if length(active_servers) > hosna_Hmax
        % Penalize infeasible solutions
        total_cost = total_cost + 1e6 * (length(active_servers) - hosna_Hmax);
    end

    z = total_cost;
end

function [y1, y2] = SinglePointCrossover(x1, x2)
    nVar = numel(x1);
    c = randi([1, nVar-1]);  % Number of Cut
    y1 = [x1(1:c) x2(c+1:end)];  % Crossover function
    y2 = [x2(1:c) x1(c+1:end)];
end

function y = MutateValidChromosome(x, K, Hmax)
    % Mutate chromosome while ensuring feasibility
    y = x;
    nVar = numel(x);
    j = randi([1, nVar]);
    y(j) = randi([1, K]);
    % Ensure Hmax constraint                  %%% infitie loop
%     while numel(unique(y)) > Hmax
%         y(j) = randi([1, K]);
%     end
end
```

```matlab
function x = InitializeValidChromosome(A, K)
    % Initialize a valid chromosome
    x = randi([1, K], [1, A]);
%     [r, f, v] = ordernrank(x);
%     %%%% Show Table %%%%%%%%%%%%
% %     table(r, f, v, 'VariableNames', {'Rank', 'Occurrence', 'Value'})
%     freqS = v(1:Hmax,1).'

%%%%%% GRAPH %%%%%%%%%%%%
%     bar(r, f, 'r')
%     grid on
%     ylim([0 1.1*max(f)])
%     set(gca, 'FontName', 'Times New Roman', 'FontSize', 14)
%     xlabel('Rank')
%     ylabel('Occurrences')
%     title('Frequency of occurrence vs. the rank of the data')
%     commandwindow



end




% Input:
% x - data vector;
%
% Output:
% r - vector with ranks of the ordered frequencies of occurrence;
% f - vector with ordered frequencies of occurrence of the unique data values;
% v - vector with the unique data values ordered by the frequency of occurrence.
function [r, f, v] = ordernrank(x)
    % represent x as column vector
    x = x(:);
    % find the unique data values
    x_unq = unique(x);
    % find the frequency of occurance of every unuque data value
    x_cnt = histc(x, x_unq);
    % order the unuque data values by frequency of occurrence
    X = sortrows([x_cnt(:) x_unq(:)], 1, 'descend');
    % form the function output
    r = transpose(1:length(x_unq));
    f = X(:, 1);
    v = X(:, 2);
end

%% Allocation Plot: S vs DS, F, RC, U

x = BestSol.Position;   % Final best chromosome

% Indices of each customer type
idx_DS = 1:nDS;
idx_F  = nDS + (1:nF);
idx_RC = nDS + nF + (1:nRC);
```

```
idx_U  = nDS + nF + nRC + (1:nU);

% Initialize allocation matrix
Alloc = zeros(K,4);
% Columns: [DS, F, RC, U]

for s = 1:K
    Alloc(s,1) = sum(x(idx_DS) == s); % DS
    Alloc(s,2) = sum(x(idx_F)  == s); % F
    Alloc(s,3) = sum(x(idx_RC) == s); % RC
    Alloc(s,4) = sum(x(idx_U)  == s); % U
end

%% Allocation Plot: S vs DS, F, RC, U

x = BestSol.Position;   % Final best chromosome

% Indices of each customer type
idx_DS = 1:nDS;
idx_F  = nDS + (1:nF);
idx_RC = nDS + nF + (1:nRC);
idx_U  = nDS + nF + nRC + (1:nU);

% Initialize allocation matrix
Alloc = zeros(K,4);
% Columns: [DS, F, RC, U]

for s = 1:K
    Alloc(s,1) = sum(x(idx_DS) == s); % DS
    Alloc(s,2) = sum(x(idx_F)  == s); % F
    Alloc(s,3) = sum(x(idx_RC) == s); % RC
    Alloc(s,4) = sum(x(idx_U)  == s); % U
end

% Plot stacked bar chart
figure;
bar(Alloc,'stacked','LineWidth',1.2);
grid on;

xlabel('Server Number (S)');
ylabel('Number of Assigned Customers');
title('Allocation of Customers to Servers');

legend({'DS','F','RC','U'}, 'Location','best');

set(gca,'XTick',1:K);
set(gca,'FontName','Times New Roman','FontSize',14);


%% GIS-Style Allocation Map (Server → DS / F / RC / U)

x = BestSol.Position;   % Final best chromosome

figure; hold on; grid on;
```

```
% === Plot Servers ===
plot(lonS, latS, 'ks', 'MarkerSize', 10, 'LineWidth', 2);

% === Plot Customers by Type ===
plot(lonDS, latDS, 'ro', 'MarkerSize', 6, 'MarkerFaceColor','r');
plot(lonF,  latF,  'b^', 'MarkerSize', 7, 'MarkerFaceColor','b');
plot(lonRC, latRC, 'gd', 'MarkerSize', 7, 'MarkerFaceColor','g');
plot(lonU,  latU,  'mo', 'MarkerSize', 6, 'MarkerFaceColor','m');

% === Draw Assignment Lines ===
for i = 1:A
    s = x(i);   % Assigned server

    plot([lonC(i), lonS(s)], ...
         [latC(i), latS(s)], ...
         'k-', 'LineWidth', 0.5);
end

xlabel('Longitude');
ylabel('Latitude');
title('GIS-Style Allocation Map: Customers Assigned to Servers');

legend({'Servers (S)','DS','F','RC','U'}, 'Location','best');

axis equal;
set(gca,'FontName','Times New Roman','FontSize',14);

%% Allocation Evolution over Iterations (Demand-weighted)

% Preallocate: iteration × server
DemandEvolution = zeros(MaxIt, K);

for it = 1:MaxIt
    x_it = BestPosHistory(it,:);
    for s = 1:K
        DemandEvolution(it,s) = sum(d(x_it == s));
    end
end

figure;
imagesc(DemandEvolution');
colorbar;
xlabel('Iteration');
ylabel('Server Number (S)');
title('Evolution of Demand Allocation to Servers');

set(gca,'YTick',1:K);
set(gca,'FontName','Times New Roman','FontSize',14);
```

Appendix B. ArcGIS Pro Network Analysis Script (Python)

The following script was used to automate the extraction of the distance matrix within ArcGIS Pro. It utilizes the arcpy.nax module to calculate the real-world road distances between potential hubs and all demand nodes in the network.

In this script, the Hubs, H are set as origins because the GA algorithm needs to know the distance from potential hubs to all other nodes to evaluate the fitness of a specific site. The coordinates you provided for DS, F, RC, and U are loaded as destinations to create a complete cost-distance profile of the Québec region.

Environment:

```
import arcpy
import os

# Set environment and workspace
arcpy.env.workspace = r"C:\YourProject\Quebec_Steel_RSC.gdb"
network_dataset = "Transportation_ND"

# Define the input feature classes (Nodes)
hubs = "Hubs_H"
decon_sites = "Deconstruction_Sites_DS"
factories = "Factories_F"
recycling_centers = "Recycling_Centers_RC"
end_users = "End_Users_U"

# Combine all demand nodes into a single destination list for the matrix
destinations = [decon_sites, factories, recycling_centers, end_users]

print("Initializing Network Analysis: OD Cost Matrix...")
# 1. Instantiate the OD Cost Matrix solver
od_solver = arcpy.nax.OriginDestinationCostMatrix(network_dataset)

# 2. Set Travel Mode and Units
# Travel mode 'Driving Distance' ensures minimization of km rather than time
od_solver.travelMode = "Driving Distance"
od_solver.distanceUnits = arcpy.nax.DistanceUnit.Kilometers

# 3. Load Origins (Potential Hub Locations)
od_solver.load(arcpy.nax.OriginDestinationCostMatrixInputDataType.Origins, hubs)

# 4. Load Destinations (DS, F, RC, and U nodes)
for ds in destinations:
    od_solver.load(arcpy.nax.OriginDestinationCostMatrixInputDataType.Destinations, ds)
```

```
# 5. Solve the Network Analysis
result = od_solver.solve()

# 6. Export the resulting distance matrix to CSV for use in MATLAB GA
if result.solveSucceeded:
    output_table = "RSC_Distance_Matrix_Results"
    result.export(arcpy.nax.OriginDestinationCostMatrixOutputType.Lines, output_table)

    # Convert GDB Table to CSV
    arcpy.management.CopyRows(output_table, "RSC_Distance_Matrix.csv")
    print("Success: Distance matrix exported to RSC_Distance_Matrix.csv")
else:
    print("Solve Failed. Check network connectivity or travel mode settings.")
    print(result.getMessages())
```