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ADVANCING CIRCULAR CONSTRUCTION IN SYDNEY: INTEGRATING SYSTEM DYNAMICS, EVOLUTIONARY GAME THEORY, AND ROBUST OPTIMIZATION FOR CONSTRUCTION AND DEMOLITION WASTE MANAGEMENT

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To my dearest wife and parents.

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Certificate of Originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work.

This thesis has not been submitted for any degree or other purposes.

I declare that any contribution made to the research by others, with whom I have worked at the University of Sydney or elsewhere, is explicitly acknowledged in the thesis.

Ze Wang

Use of generative artificial intelligence

During the preparation of the thesis, the author used ChatGPT for the purposes of text enhancement. The use of this generative AI tool includes sentence structure and spelling. The author confirms that where text was modified by generative AI, the content was reviewed for possible errors, inaccuracies, and bias. The author takes full responsibility for the submitted thesis and ensures the work is their own and has used generative AI within the parameters of use (refer to the University of Sydney generative AI guide for researchers).

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Publications and Research Works

This thesis is based on the research papers:

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Authorship Attribution Statement. The three works included in the thesis reflect collaborative efforts. For all the works, I made the main contributions by deriving the theoretical results, conducting the majority of the experiments, and writing the drafts. The co-authors have helped formulate the ideas in the early stage, design the models and experiments, as well as refine the works.

Ze Wang, 30/04/2025

Supervisor Statement. As the supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

Michael Bell, 30/04/2025

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Abstract

The construction sector not only drives global economic growth but also ranks among the world's largest consumers of natural resources and producers of waste. With construction activities responsible for 30–50% of the world's raw material use and nearly 37% of energy-related emissions, there is an urgent need to pivot from the linear "take-make-dispose" model to a circular economy that emphasizes resource efficiency and closed-loop processes. However, implementing such circular strategies is particularly challenging in dense urban contexts like Sydney, where construction and demolition waste levels remain critically high.

This dissertation tackles these challenges by proposing and evaluating innovative approaches to circular construction. Employing a multi-method framework that integrates System Dynamics modeling, evolutionary game theory, and distributionally robust optimization, the research pursues three interrelated objectives. First, it explores the economic and operational drivers affecting concrete recycling in Sydney. Second, it assesses how stakeholder interactions and targeted policies can accelerate the adoption of sustainable construction practices. Third, it optimizes skip-based waste collection under uncertainty, offering more resilient and efficient logistics for construction and demolition waste management.

The findings contribute both theoretically and practically to the field of circular construction. They highlight key leverage points to increase recycling rates, offer evidence-based policy insights for promoting sustainable practices, and present robust operational solutions for waste management. Taken together, these results furnish actionable guidance for policymakers and industry professionals eager to operationalize circular economy principles, thus bridging a crucial gap between sustainability concepts and on-the-ground construction practices.

CHAPTER 1

Introduction

The global community faces significant environmental challenges from climate change, resource depletion, and waste accumulation that require comprehensive solutions beyond conventional economic models. The circular economy has emerged as a promising framework, offering a regenerative alternative to the traditional linear 'take-make-dispose' model that has characterized industrial activity since the Industrial Revolution Geissdoerfer et al. [2017]. This transition is especially critical for the construction sector, which accounts for approximately 40% of global carbon emissions, 40% of primary resource consumption, and one-third of all waste generated worldwide Pomponi and Moncaster [2017], Adams et al. [2017]. While the conceptual foundations of circular construction are increasingly established, translating these principles into operational practices remains challenging, particularly in the Australian context.

1.1 The Circular Economy: From Concept to Construction

1.1.1 A Transformative Economic Paradigm

The circular economy represents an innovative approach to economic development aimed at sustainable growth decoupled from finite resource consumption, emphasizing resource efficiency, waste minimization, and long-term environmental protection Murray et al.

[2017], Babbitt et al. [2018]. It constitutes a fundamental reconceptualization of economic activities, where material flows are designed to be restorative and regenerative by intention Kirchherr et al. [2017]. In contrast to traditional linear economic models—characterized by extraction, consumption, and disposal—the circular economy prioritizes reuse, repair, refurbishment, remanufacturing, and recycling to maintain resource value and reduce environmental impacts Hofmann [2019], Bao [2023], Bigliardi et al. [2022]. This paradigm further seeks the regeneration of natural systems, enhancing biodiversity and ecosystem health Luthra et al. [2022], Bianchi and Cordella [2023].

The concept has evolved significantly since its academic origins in the 1970s, influenced by diverse schools of thought including industrial ecology, cradle-to-cradle design, biomimicry, and performance economy Korhonen et al. [2018]. The interconnection between economic systems and environmental sustainability is particularly evident in resource-intensive sectors like construction, which accounts for approximately 13% of global GDP and employs around 7% of the world's workforce RYFAN [2018].

The transition toward circularity has gained significant momentum in recent years, catalyzed by growing resource constraints, increasing environmental awareness, and economic opportunities. Major economies including the European Union, China, and Australia have incorporated circular principles into their policy frameworks, with the EU's Circular Economy Action Plan representing one of the most comprehensive policy initiatives to date European Commission [2020]. Simultaneously, leading corporations across sectors have begun adopting circular business models, recognizing both the sustainability imperative and commercial advantages of circularity World Economic Forum [2022].

Despite this progress, the implementation of circular economy principles remains at a nascent stage, with significant technical, economic, institutional, and social barriers to overcome. The transition requires not only technological innovation but also profound changes in consumption patterns, business models, and governance systems Kirchherr et al. [2017], Korhonen et al. [2018]. These challenges are particularly pronounced in complex, material-intensive sectors like construction, where long-established practices and extensive value chains complicate transformation efforts.

1.1.2 Reimagining the Built Environment

The construction sector represents both a critical challenge and a tremendous opportunity for circular economy implementation Benachio et al. [2020]. As urbanization accelerates globally, with an estimated 230 billion square meters of new construction expected by 2060—equivalent to adding a new Paris to the world every week—the environmental implications of conventional construction practices become increasingly unsustainable Material Economics [2018]. The built environment's substantial material footprint, combined with buildings' long lifespans and complex material compositions, makes the sector a priority focus for circular interventions.

Construction and demolition activities generate approximately 35% of global waste, with much of this material ending up in landfills despite significant potential for recovery and reuse Caro et al. [2024]. The sector's environmental impact extends beyond waste generation to encompass substantial greenhouse gas emissions, water consumption, and biodiversity loss. The embodied carbon in building materials—carbon emissions associated with material extraction, manufacturing, transportation, and construction—represents an increasing proportion of buildings' lifecycle emissions as operational energy efficiency improves Caro et al. [2024]. These environmental externalities, coupled with growing resource scarcity and volatility in material markets, create compelling imperatives for transitioning toward more circular approaches in construction Adams et al. [2017], Hart et al. [2019].

Circular construction encompasses a range of strategies and approaches aimed at minimizing resource inputs and waste outputs throughout a building's lifecycle. These include design for disassembly and adaptability, material selection based on recyclability and regenerative potential, modular construction techniques, building material passports, and innovative business models such as product-service systems for building components Buildings as Material Banks [2019], Akanbi et al. [2018]. Digital technologies like Building Information Modeling (BIM), material scanning, and blockchain-based material tracking systems are increasingly enabling these circular approaches by facilitating information flow and traceability across the building lifecycle Akanbi et al. [2018], Benachio et al. [2020].

The potential economic benefits of circular construction are substantial. A study by the Ellen MacArthur Foundation estimates that circular approaches in the built environment could reduce construction costs by up to 18% by 2030 while creating new revenue streams through innovative business models and secondary material markets. Beyond economic advantages, circular construction offers significant environmental benefits, including reduced resource extraction, lower carbon emissions, decreased waste generation, and enhanced ecosystem health Hossain and Ng [2020]. Social benefits include improved occupant health and wellbeing, job creation in remanufacturing and material recovery, and enhanced community resilience through more adaptable built environments Munaro et al. [2020].

Pioneering projects across Europe, North America, and Asia have begun demonstrating the practical viability of circular construction principles, from Madaster's material passport platform in the Netherlands to Arup's circular building prototypes in the United Kingdom Leising et al. [2018]. These initiatives highlight both the technical feasibility and potential benefits of circular construction, including reduced environmental impacts, enhanced resource security, and new value creation opportunities. However, they also reveal significant implementation barriers, including fragmented industry structures, skills gaps, regulatory constraints, and economic challenges related to upfront costs and value capture mechanisms Adams et al. [2017].

1.1.3 The Australian Context: Opportunities and Challenges

Australia's distinctive geography, urban development patterns, and regulatory environment create both unique challenges and opportunities for implementing circular construction principles. The large distances between urban centers intensify logistics considerations, while the concentration of population in coastal cities creates concentrated waste streams that could potentially support localized circular material economies.

In Australia, the construction industry contributes approximately 8% to the national GDP while generating around 20.4 million tonnes of waste annually, accounting for approximately 40% of the country's total waste stream Australian Bureau of Statistics [2024]. In New South Wales (NSW) specifically, the construction sector produces approximately 9.8 million tonnes of construction and demolition waste (C&DW) annually, achieving a recycling rate of 79.6% Australian Government Department of Climate Change and Water [2022]. Despite this relatively high recycling rate, transportation and logistical challenges often hinder broader adoption of recycled aggregates, particularly in urban environments like Sydney Hameed and Chini [2013], Ghaffar et al. [2020], Zhuonan [2015], Xing et al. [2022].

Concrete, the predominant construction material in Australia, significantly contributes to both material consumption and waste generation, making its effective management crucial for achieving sustainability goals Cement Concrete & Aggregates Australia [2023], Aïtcin [2000], Tam et al. [2018]. Achieving global climate targets, such as those set by the International Panel on Climate Change (IPCC) for net-zero greenhouse gas emissions by 2050, necessitates transformative changes in building design, lifecycle management, and waste reduction strategies Kirchherr et al. [2017].

The Australian government has recognized the strategic importance of circular approaches in construction through policy frameworks such as the National Waste Policy

Action Plan and the National Construction Code, which increasingly incorporate sustainability requirements Department of Agriculture and the Environment [2020]. State-level initiatives, particularly in New South Wales and Victoria, have established targets for construction waste diversion and material recovery, supported by infrastructure investments in recycling facilities and economic instruments such as landfill levies Authority [2025]. These policy interventions aim to address the historical reliance on landfilling that has characterized Australia's waste management approach for decades.

Leading Australian construction firms and industry bodies have begun embracing circular principles through initiatives such as the Green Building Council of Australia's Green Star rating system, which rewards circular design strategies, and the Infrastructure Sustainability Council's IS Rating Tool, which includes material circulation criteria of Australia [2025], Department of Climate Change and [DCCEEW]. Research institutions, including the CSIRO and various universities, are actively developing circular construction technologies and methodologies adapted to Australian contexts, climate conditions, and material availability.

Despite these positive developments, significant barriers to circular construction implementation persist in Australia. These include regulatory inconsistencies across jurisdictions, limited awareness and technical knowledge among industry practitioners, insufficient market demand for circular building products, and economic structures that fail to internalize environmental costs Shooshtarian et al. [2020]. The geographic dispersion of Australia's population centers also creates logistical challenges for material recovery and redistribution, particularly in regional and remote areas.

The Australian context offers both unique challenges and opportunities for circular construction implementation. The country's high urbanization rate (with over 86% of the population living in urban areas), substantial construction activity in rapidly growing cities, and growing environmental awareness create favorable conditions for circular innovation Australian Bureau of Statistics [2024]. Simultaneously, Australia's resource-intensive economy, extensive raw material extraction industries, and historical reliance on landfilling present entrenched barriers to circularity.

1.2 The Critical Role of Logistics in Circular Construction

A critical yet often overlooked component of circular construction is the transportation and logistics system that enables material flows between construction sites, recycling facilities, and markets for secondary materials. Transportation significantly influences the sustainability and economic efficiency of construction operations, particularly in the context of concrete production and waste management Dubois and Hulthén [2018], Knoeri et al. [2013]. Efficient logistics can markedly reduce project costs and environmental impacts, underscoring the need for strategic planning and optimization Marinković et al. [2010], Xiao et al. [2018].

In the Australian context, where urban centers are widely dispersed and construction waste often travels considerable distances to processing facilities, logistics optimization represents a particularly important leverage point for improving circular construction outcomes. The "hidden emissions" associated with waste transportation can substantially reduce the net environmental benefits of material recycling, especially when inefficient routing or vehicle utilization patterns prevail Ghaffar et al. [2020], Hart et al. [2019].

Emerging technologies, such as electric trucks, offer promising solutions to address transportation-related environmental challenges Donnelly [2022]. Electric trucks, characterized by zero emissions, lower operating costs, and reduced noise pollution, are increasingly suitable for urban logistics despite current limitations in battery range and cost Nykvist and Olsson [2021]. Technological advancements and supportive regulatory frameworks are expected to accelerate the adoption of electric vehicles within the construction sector, enhancing sustainability and operational efficiency European Commission [2019].

The optimization of transportation and logistics systems—particularly for skip-based waste collection services that form the backbone of C&D waste management—represents a critical operational aspect of implementing circular construction principles in practice. Effective skip logistics directly supports circular economy principles by enabling the efficient collection, transportation, and processing of construction and demolition waste—transforming what would otherwise be landfill material into valuable secondary resources. By optimizing skip operations, one can address a fundamental challenge in implementing circular construction: the practical logistics of material recovery.

1.3 Research Gaps and Novelty

Despite growing interest in circular construction, **a fundamental disconnect exists** between theoretical circular economy principles and their practical, operational implementation in the construction sector. This thesis addresses three critical, interconnected gaps that collectively hinder the transition to circular construction practices.

1.3.1 Gap 1: System-Level Understanding of Material Flow Dynamics

While previous studies have examined individual components of concrete recycling Pomponi and Moncaster [2017], Adams et al. [2017], **no existing research has developed** integrated models that capture the complex, dynamic interactions between economic factors, policy interventions, and material flows in real urban contexts. **This gap has significant practical implications**: without understanding these dynamic interactions, policymakers cannot effectively design interventions that account for unintended consequences and feedback effects.

Novel Contribution: This thesis develops the first System Dynamics model specifically calibrated for concrete recycling dynamics in Sydney, quantifying how economic factors, logistical constraints, and policy interventions interact to influence recycling rates and resource conservation.

1.3.2 Gap 2: Stakeholder Behavior in Sustainability Transitions

Existing research on stakeholder behavior in green construction has primarily focused on static analyses or single-stakeholder perspectives Li et al. [2022c], Hao et al. [2019]. **A critical gap remains** in understanding how multiple stakeholders (government, developers, customers) interact and co-evolve their strategies in response to changing policy incentives and market conditions. **Notably absent from the literature** is any framework that combines behavioral modeling with system-level dynamics.

Novel Contribution: This research introduces the first integration of evolutionary game theory with system dynamics modeling to analyze stakeholder interactions in green construction adoption, revealing emergent behaviors and optimal policy combinations.

1.3.3 Gap 3: Uncertainty-Aware Operational Optimization

While skip logistics optimization has been studied Archetti and Speranza [2005], Belenguer et al. [2024], existing approaches fail to address two critical limitations: (1) they assume trucks can carry multiple containers simultaneously, incompatible with C&D skip services, and (2) **no existing framework** incorporates the inherent uncertainties in travel times and demand patterns that characterize real-world operations.

Novel Contribution: This thesis presents the first distributionally robust optimization framework specifically designed for skip services, addressing practical challenges while accounting for real-world uncertainties.

1.3.4 The Integration Gap: A Multi-Scale Approach

The central innovation of this research lies not only in addressing each gap individually, but in examining their interconnections. While material flows, stakeholder behaviors, and operational logistics have typically been studied in isolation, **this thesis is the first to provide a comprehensive, multi-scale analysis** that reveals how these dimensions influence each other in circular construction implementation.

1.4 Research Objectives

This research adopts a multi-scale approach to examine circular construction implementation, progressing from material system dynamics (concrete recycling), to stakeholder behavior analysis (policy and market factors), to operational logistics optimization (skip management). This comprehensive strategy enables a holistic understanding of the interrelated technical, economic, social, and logistical factors that collectively determine the success of circular economy implementation in construction.

Specifically, this thesis addresses three interconnected objectives:

(1) **To explore the complex dynamics of concrete recycling in Sydney's construction sector** through a System Dynamics approach, investigating how economic factors, logistical constraints, and policy interventions influence recycling rates, landfill accumulation, and resource conservation.

This objective is accomplished in Chapter 3: "Exploring the Dynamics of Concrete Recycling in Circular Construction," which develops and validates *a comprehensive SD model calibrated specifically for Sydney's construction sector.*

(2) **To analyze the interactions between key stakeholders**—government bodies, developers, and customers—in promoting green construction practices using a novel combination of evolutionary game theory and system dynamics modeling, with emphasis on evaluating the effectiveness of various policy instruments such as green taxes, public awareness campaigns, and financial incentives.

This objective is addressed in Chapter 4: "System Dynamics Analysis of Stakeholder Behavior in Green Construction Adoption," which integrates evolutionary game theory with system dynamics to examine stakeholder interactions and policy effectiveness.

(3) **To optimize operational aspects of C&D waste management** through the development of a distributionally robust scheduling framework for skip services, addressing practical challenges like travel time uncertainties, vehicle routing constraints, and facility location decisions.

This objective is fulfilled in Chapter 5: "Optimizing Skip Schedules for Construction and Demolition Waste Management Under Uncertainty," which presents a novel DRO framework for skip logistics optimization.

This multi-faceted approach provides a comprehensive examination of circular construction from theoretical, strategic, and operational perspectives, aiming to identify practical pathways toward more sustainable building practices in urban environments. The sequential progression from system-level dynamics (Chapter 3) to stakeholder behaviors (Chapter 4) to operational implementation (Chapter 5) creates a logical flow that builds understanding from macro-level patterns to micro-level operational solutions.

1.5 Methodological Innovation and Contributions

This research makes three distinct methodological contributions to the circular construction literature:

(1) **First System Dynamics Model for Urban Concrete Recycling**: Develops and validates a comprehensive SD model specifically calibrated for Sydney's construction sector, providing quantitative insights into recycling dynamics.
(2) **Novel Integration of Game Theory and System Dynamics**: Combines evolutionary game theory with system dynamics in an innovative approach that reveals stakeholder behavior emergence in sustainability transitions.
(3) **First Distributionally Robust Framework for Skip Logistics**: Introduces uncertainty-aware optimization specifically designed for construction waste management, addressing real-world operational challenges.

Collectively, these contributions provide both theoretical advancement and practical tools for implementing circular construction principles at multiple scales.

1.6 Thesis Structure

This thesis is structured to systematically address the research objectives through a progression of interrelated studies, each examining distinct yet complementary aspects of circular construction:

Chapter 2: Literature Review summarizes the existing literature on circular economy principles, concrete recycling, stakeholder behavior, and logistics optimization under uncertainty. By reviewing these strands of research, the chapter establishes both the conceptual foundation and methodological tools available for studying circular construction. *This chapter provides the theoretical foundation for all three research objectives by* *identifying gaps in system dynamics applications, stakeholder behavior modeling, and uncertainty handling in logistics.*

Chapter 3: Exploring the Dynamics of Concrete Recycling in Circular Construction *(addresses Objective 1)* investigates the complex interplay between economic factors and operational constraints in Sydney's concrete recycling sector. Using System Dynamics modeling, this chapter uncovers nonlinear relationships between recycling costs, landfill fees, logistics expenses, and their collective influence on recycling rates and resource conservation. *The chapter delivers a calibrated SD model that quantifies recycling dynamics and evaluates policy intervention scenarios.*

Chapter 4: System Dynamics Analysis of Stakeholder Behavior in Green Construction Adoption *(addresses Objective 2)* expands the analytical framework by integrating evolutionary game theory with system dynamics to examine stakeholder behaviors in green construction adoption. This chapter evaluates various policy instruments—including dynamic taxation strategies, public awareness campaigns, and green financing mechanisms—to identify optimal approaches for promoting sustainable practices. *The chapter provides empirical insights into stakeholder interactions and policy effectiveness through the novel integration of game theory and system dynamics.*

Chapter 5: Optimizing Skip Schedules for Construction and Demolition Waste Management Under Uncertainty *(addresses Objective 3)* addresses operational challenges in waste management through the development of a distributionally robust optimization model for skip services. This chapter presents practical solutions for efficient vehicle routing, schedule optimization, and facility allocation while accounting for travel time uncertainties in urban environments. *The chapter delivers a robust optimization framework with demonstrated performance improvements over conventional approaches.*

Chapter 6: Discussion and Implementation *(integrates findings from Objectives 1-3)* synthesizes the findings from the system dynamics, evolutionary game theory, and optimization analyses to show how economic incentives and stakeholder behavior jointly drive improvements in recycling practices. It highlights that strategic adjustments—such as aligning cost differentials and policy measures—can trigger significant shifts toward circular construction. *This chapter demonstrates how the three analytical approaches complement each other to provide comprehensive insights for circular construction implementation.*

Chapter 7: Conclusion *(synthesizes contributions from all objectives)* succinctly summarizes the study's contributions and outlines directions for further research. It emphasizes that the combined approach of system dynamics, game theory, and robust optimization provides actionable insights for transforming construction waste management. *The chapter consolidates the theoretical, methodological, and practical contributions of the research.*

While each chapter employs distinct methodologies—system dynamics modeling (Chapter 3), evolutionary game theory integration (Chapter 4), and distributionally robust optimization (Chapter 5)—they together address the multifaceted challenges of circular construction. The economic and technical groundwork established in Chapter 3 contextualizes the stakeholder behaviors examined in Chapter 4, while the operational solutions developed in Chapter 5 specifically target the logistical barriers identified in both preceding chapters.

CHAPTER 2

Literature Review

2.1 Related Literature

This chapter reviews the existing body of literature relevant to circular economy and construction, with a particular focus on concrete recycling, stakeholder behavior, and logistics optimization under uncertainty. It synthesizes prior research to establish the theoretical and empirical foundations of this thesis, while also identifying the specific gaps that motivate the subsequent chapters.

Circular economy and circular construction. Foundational work frames the circular economy (CE) as a regenerative alternative to linear production–consumption systems, emphasizing restorative material flows and the hierarchy of reuse, repair, remanufacturing, and recycling [Murray et al., 2017, Kirchherr et al., 2017, Korhonen et al., 2018, Hofmann, 2019, Babbitt et al., 2018, Bao, 2023]. Within the built environment, reviews synthesize strategies such as design for disassembly/adaptability, building material passports, modular construction, and circular business models [Benachio et al., 2020, Buildings as Material Banks, 2019, Leising et al., 2018]. Empirical and policy analyses highlight the scale of the challenge for construction—large material and carbon footprints, significant C&D waste shares, and growing attention in EU/Australian policy [Pomponi and Moncaster, 2017, European Commission, 2020, Adams et al., 2017, Caro et al., 2024]. Digital enablers (BIM, traceability) are recognized as levers for material circularity [Akanbi et al., 2018, Benachio et al., 2020]. Despite this momentum, prior syntheses largely remain conceptual or technology-scanning and seldom connect CE principles to the *operational economics and logistics* that govern waste routing in practice.

Concrete recycling and recycled aggregate use. Concrete dominates the Australian material footprint, with RAC positioned as a viable substitute for virgin aggregate in appropriate mixes [Cement Concrete & Aggregates Australia, 2023, Tam et al., 2018]. Technical studies investigate RAC performance, processing, and quality control along the concrete chain [Tam, 2009, Ohemeng and Ekolu, 2020, Zhao et al., 2021]. Barriers frequently cited include logistics costs, dispersion of facilities, and perceived variability—factors that directly shape contractors' routing choices between recycling and landfill [Hameed and Chini, 2013, Ghaffar et al., 2020, Marinković et al., 2010, Xiao et al., 2018]. Prior work, however, typically treats these cost components as *static* or case-specific rather than modeling their *dynamic* feedbacks at city scale.

System dynamics (SD) for C&D waste and policy. SD has been used to explore policy levers in waste minimization, levy design, and recycling programs, revealing path dependence and delayed responses in urban waste systems [Forrester, 1994, Ding et al., 2018, Hao et al., 2019, Mak et al., 2019, Jia et al., 2018]. These studies validate SD's suitability for capturing feedback-rich material flows. Yet, the *joint* evolution of (i) recycling fees, (ii) landfill levies, and (iii) *logistics costs*—and their combined effect on routing shares, landfill accumulation, and virgin aggregate extraction—has not been explicitly integrated into a calibrated SD model for concrete waste in Sydney.

Stakeholder behavior and adoption of green construction. Behavioral and institutional drivers—developers, government, customers, and recyclers—critically mediate the uptake of circular practices. Evolutionary/game-theoretic models have been used to study incentive compatibility and adoption dynamics under taxes, subsidies, and awareness campaigns [Li et al., 2022c]. Prior analyses typically remain decoupled from material-flow dynamics; conversely, SD applications often aggregate behavior into coarse response functions. There is room for *hybrid* approaches that connect stakeholder strategy evolution with system-level stock-flow consequences.

Skip logistics and vehicle-routing variants. C&D skip operations differ from classical roll-on/roll-off routing models that assume multi-container capacity and simple out-and-back patterns [Li et al., 2018, Wøhlk and Laporte, 2022, Belenguer et al., 2024, Wy et al., 2013]. Empirical practice in skip services is dominated by *single-unit capacity*, time-dependent rentals, and compound trips (deliver empty, collect full, tip at facility), with driver-hour and spatial-radius constraints [Rabbani et al., 2016, Yazdani et al., 2021, Archetti and Speranza, 2005, Aringhieri et al., 2018, De Meulemeester et al., 1997]. Existing formulations seldom incorporate (a) decision-relevant *travel-time uncertainty* and (b) *city-scale coupling* to recycling versus landfill economics.

Optimization under uncertainty. Stochastic programming (SP) requires distributional assumptions that are often fragile in urban logistics [Shapiro et al., 2021, Birge and Louveaux, 2011]; robust optimization (RO) can be overly conservative [Ben-Tal and Nemirovski, 2000, Bertsimas and Sim, 2004]. Distributionally robust optimization (DRO), including Wasserstein and decision-dependent ambiguity sets, balances tractability and protection against misspecification [Rahimian and Mehrotra, 2022, Carlsson et al., 2018, Basciftci et al., 2021]. While DRO has matured in freight and facility planning, its application to *skip* scheduling with realistic service patterns and coupling to circular-economy outcomes remains limited.

Synthesis and research gap. Across these streams, three limitations recur: (i) a shortage of *calibrated, feedback-aware* city models linking recycling/landfill fees with *logistics costs* and material outcomes (recycling share, landfill mass, virgin extraction);

(ii) limited *behavior–system* integration that ties stakeholder incentive dynamics to measurable stock–flow consequences; and (iii) a lack of *uncertainty-aware* formulations for single-unit skip operations reflecting realistic duty cycles.

This thesis addresses these gaps by: (1) developing a Sydney-calibrated SD model that endogenizes routing shares via a cost-sensitive choice function and traces knock-on effects on landfill accumulation and gravel extraction; (2) integrating evolutionary/behavioral analysis to evaluate policy mixes (levies, subsidies, awareness) alongside system responses; and (3) proposing a distributionally robust scheduling framework for skip services under travel-time uncertainty with operational constraints characteristic of C&D waste logistics.

CHAPTER 3

The Dynamics of Concrete Recycling in Circular Construction: A System Dynamics Approach in Sydney Australia

3.1 Introduction

Building on the circular construction framework established in Chapter 1, this chapter focuses specifically on the concrete recycling supply chain and its complex economic dynamics. While Chapter 1 highlighted the general challenges of implementing circular economy principles in construction, this chapter addresses a critical knowledge gap: understanding how recycling costs, landfill fees, and logistics costs interact dynamically through nonlinear feedback loops to collectively shape recycling and landfilling rates in the construction industry.

In the Australian context, concrete represents a particularly significant component of construction and demolition (C&D) waste streams. New South Wales alone generates approximately 9.8 million tonnes of C&D waste annually, with a recycling rate of 79.6% [Australian Government Department of Climate Change and Water, 2022]. However, concrete debris constitutes a major portion of this waste, with approximately 29 million cubic meters of concrete used annually in Australia [Cement Concrete & Aggregates Australia, 2023]. While recycling this material into recycled aggregate concrete (RAC) offers clear environmental and economic benefits [Tam et al., 2018, Ohemeng and Ekolu, 2020, Zhao et al., 2021], practical implementation faces significant barriers including high logistics costs and additional processing requirements [Hameed and Chini, 2013, Marinković et al., 2017].

The concrete recycling supply chain involves multiple stakeholders—from waste generators and recyclers to concrete manufacturers and construction contractors—each responding to different economic incentives [Shooshtarian et al., 2020]. Economic drivers are frequently identified as the most critical determinants of whether materials are recycled or landfilled [Alsheyab, 2022, European Environment Agency, 2019, Hua et al., 2022]. Previous system dynamics studies have examined individual aspects of this problem, including waste reduction programs [Ding et al., 2018], economic outcomes of waste minimization strategies [Hao et al., 2019], and optimal waste disposal fees [Mak et al., 2019]. However, **no prior study has explicitly examined how recycling costs, landfill fees, and logistics costs interact dynamically to collectively shape recycling outcomes in the construction industry**.

This represents a critical research gap. Understanding these intertwined factors systemically is essential for devising effective recycling policies and business strategies, yet existing research has largely considered them in isolation. A holistic investigation is needed that integrates economic incentives and logistical operations, capturing their interdependencies to identify key leverage points for increasing concrete recycling.

This chapter addresses this gap by developing a system dynamics model of the concrete recycling supply chain, using Sydney, Australia as a case study. The model captures the coupled, nonlinear feedback relationships between recycling costs, landfill charges, logistics expenses, and the resulting recycling and landfill rates. Through systematic scenario analysis, we quantitatively evaluate how changes in these economic and operational factors propagate through the system over time, identifying critical factors that drive recycling outcomes.

Research Contribution: To our knowledge, this work presents the first comprehensive system dynamics analysis of these interacting factors in a circular construction context. The insights provide direct practical value for policymakers in evaluating policy levers such as landfill levies and recycling subsidies, and for industry stakeholders in optimizing waste collection, material processing, and recycled aggregate utilization strategies.

The remainder of this chapter is structured as follows. Section 3.2 describes the methodology, including the development and validation of the system dynamics model. Section 3.3 presents the scenario design, simulation results, and discusses their policy implications. Finally, Section 2.4 concludes with key findings, study limitations, and recommendations for future research.

3.2 Methods

This section outlines the methodological framework of our study, emphasizing the System Dynamics (SD) approach used to examine the complex interactions in Sydney's concrete recycling system. We first provide an overview of System Dynamics modeling, then describe the development of our model, including key equations and parameters, and the formulation of two interconnected sub-models.

3.2.1 Development of the System Dynamics Model for the Concrete Supply Chain

System Dynamics is a modeling methodology for analyzing complex systems and their evolution over time. It synthesizes elements of systems theory, control theory, and information theory to provide a framework for understanding and solving systemic issues [Forrester, 1994]. An SD model is built to mimic real-world system behavior with the goal of revealing the system's underlying structure and key variables, rather than reproducing the system in exact detail. The modeling process is problem-driven, focusing on specific questions and well-defined objectives [Ding et al., 2018].

The development of an SD model typically begins by defining the system boundaries and identifying the main components and their interconnections. Next, one identifies the feedback loops in the system, which represent the causal relationships among components that govern the system's behavior over time [Li et al., 2022c]. The following step involves constructing a computer-based representation of the system using specialized software. In this study, we used Vensim, a widely-used tool for building and simulating SD models across domains such as business, economics, energy, environment, and healthcare [Jones, 2014]. The model is built using stocks, flows, and feedback loops, and it simulates the system's behavior over time. Simulation results are then analyzed to understand the system's dynamics and key driving factors [Jia et al., 2018]. Finally, insights from the model inform policy recommendations aimed at improving system performance.

In this study, we developed a System Dynamics model tailored to our research objectives: investigating how recycling cost, landfill cost, and logistics cost collectively influence the recycling rate and landfill rate in the construction industry. The model is intended to improve understanding of the current level of circularity in Sydney's construction sector and to explore how policy interventions could reshape the system toward greater sustainability. Figure 3.1 presents a schematic of the material flow in the construction industry with a focus on the concrete supply chain. The structure of this flow and the relationships between components were informed by literature, industry reports, and interviews with industry experts.

3.2.1.1 Sydney Concrete Production Model

Figure 3.2 illustrates the concrete production process in our model of Sydney's construction sector. In this framework, new concrete construction increases the stock of in-use

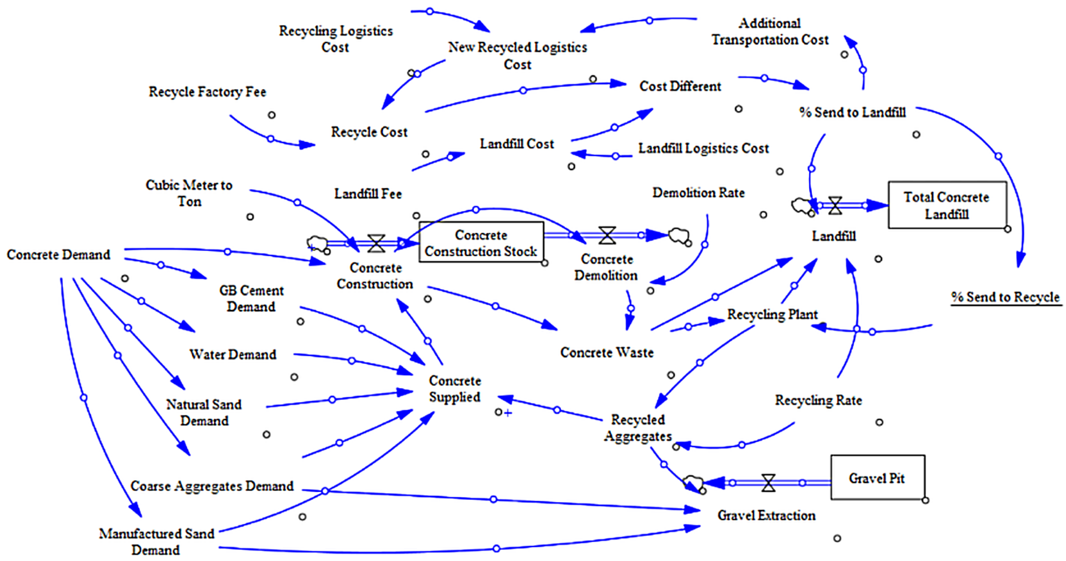


FIGURE 3.1. Sydney concrete supply chain

concrete, while demolition of concrete structures reduces that stock. Both construction and demolition activities generate concrete waste, which can either be sent to landfill or processed into recycled aggregate. The recycled aggregate is then available for use in producing new concrete, closing the materials loop.

Key Model Assumptions. The concrete production sub-model is based on several critical assumptions that require explicit justification:

(1) **Demand-Supply Equilibrium**: We assume that concrete supply always rises to meet demand without delays or capacity constraints. *Justification*: Sydney's mature construction market typically maintains sufficient production capacity to meet demand fluctuations, as confirmed through industry consultations with three major concrete suppliers.
(2) **Representative Concrete Mix**: Street Pavements N20 concrete represents all concrete production in Sydney. *Justification*: This mix (a) constitutes one of the most commonly used concrete types by volume, (b) exhibits good compatibility

with recycled aggregates, and (c) represents the primary application for recycled concrete aggregates in current practice [Wang et al., 2021].

(3) **Recycled Aggregate Substitution**: Recycled aggregates can substitute virgin coarse aggregates at a 1:1 ratio without affecting concrete performance. *Justification*: Australian Standard AS 1141 permits up to 100% substitution of virgin coarse aggregate with recycled concrete aggregate in pavement applications.

(4) **Constant Recycling Efficiency**: Recycling plants maintain a 90% processing efficiency regardless of input volumes. *Justification*: Industry interviews with five recycling facility operators indicated that modern crushing and screening equipment achieves 85-95% material recovery rates under normal operating conditions.

(5) **Fixed Demolition Rate**: The demolition rate (relative to construction activity) remains constant over the simulation period. *Justification*: While building lifespans vary, the 50-year average building life assumed reflects typical commercial and residential structures in Sydney, as documented in building stock studies.

Behavioral Assumptions in Decision-Making. The model's waste routing decisions are governed by a logistic choice function with the following behavioral assumptions:

(1) **Economic Rationality**: Contractors choose waste disposal routes based primarily on total cost (processing fee + logistics cost). *Justification*: Industry surveys consistently identify cost as the primary factor in waste management decisions, with 78% of contractors citing it as the most important criterion.

(2) **Perfect Information**: All contractors have complete knowledge of recycling and landfill costs. *Justification*: The Sydney market is mature with well-established pricing transparency through industry associations and online platforms.

(3) **Homogeneous Contractor Behavior**: All contractors respond identically to cost differentials. *Justification*: While individual variation exists, the aggregated model captures average market behavior, as validated through comparison with NSW-wide recycling statistics.

(4) **Instantaneous Adjustment**: Contractors adjust their routing decisions immediately when costs change. *Justification*: Most waste management contracts are short-term (project-based), allowing rapid response to cost changes.

3.2.2 Model Formulation

We constructed two interconnected sub-models for the Sydney concrete recycling system: the Concrete Production sub-model and the Concrete Recycling Choice sub-model. Together, these sub-models capture the material flows, economic factors, and decision processes that drive recycling behavior in the construction industry. In the following subsections, each component of the model is explained along with its key parameters, assumptions, and governing equations.

3.2.2.1 Sydney Concrete Production Model

Figure 3.2 illustrates the concrete production process in our model of Sydney's construction sector. In this framework, new concrete construction increases the stock of in-use concrete, while demolition of concrete structures reduces that stock. Both construction and demolition activities generate concrete waste, which can either be sent to landfill or processed into recycled aggregate. The recycled aggregate is then available for use in producing new concrete, closing the materials loop.

The dynamics of concrete construction in the model are driven by the interplay between concrete demand and supply. According to industry data, New South Wales (NSW) consumes approximately 9.5 million m^3 of premixed concrete annually [STAFF WRITER,

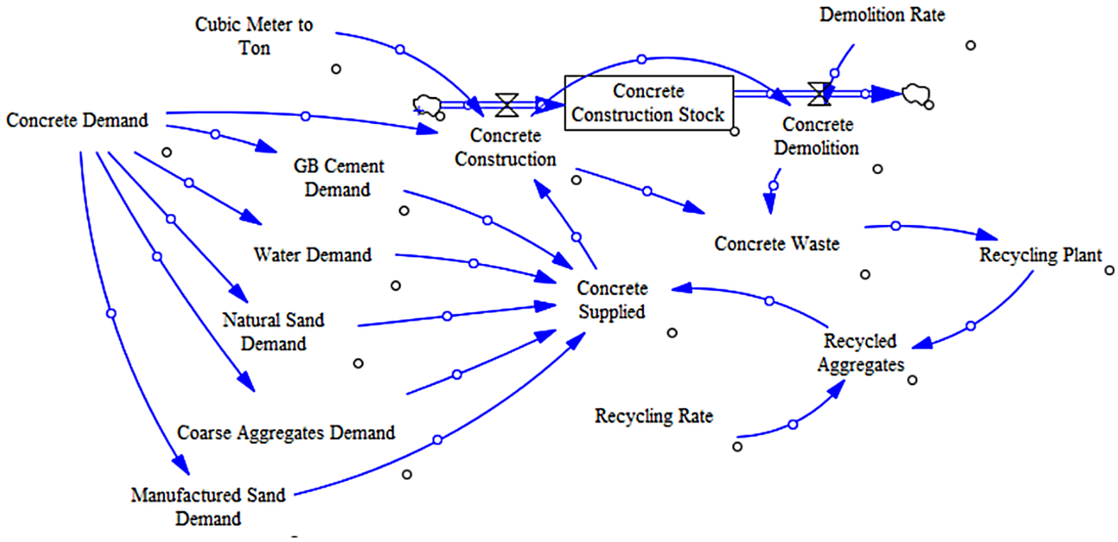


FIGURE 3.2. Sydney concrete production model

2018]. To estimate Sydney's concrete consumption, we scaled this figure by 66% to reflect Sydney's share of the NSW population [NSW GOVERNMENT, 2023]. We assumed an annual growth in concrete demand of about 2%, and the model assumes that supply always rises to meet this demand. In other words, any increase in concrete demand triggers a corresponding increase in the supply of all constituent materials required for concrete production, ensuring that demand is fully satisfied.

The specific concrete mix chosen to represent concrete production in Sydney was Street Pavements N20 concrete, the concrete mix ratio we used was documented by Mohammadi and South [2017], respectively (Table 3.1). The selection of this particular type of concrete as the representative was guided by an analysis of its composition. Notably, it is one of the more commonly used types of concrete in terms of quantity, and it exhibits a compatibility with recycled aggregate. This compatibility is particularly relevant in the current landscape, where a significant proportion of recycled aggregates are incorporated into street pavement or road base construction [Wang et al., 2021].

On the waste generation side, data from the Australian Government's Department of Climate Change, Energy, the Environment and Water indicate that NSW generated about

TABLE 3.1. Equations in SD model

Variables	**Type**	**Unit**	**Equations**
Concrete Demand	Data	m^3	/
GB Cement Demand	Auxiliary	Ton	$(240 \times \text{Concrete Demand})/1000$
Water Demand	Auxiliary	Ton	$(165 \times \text{Concrete Demand})/1000$
Natural Sand Demand	Auxiliary	Ton	$(\text{Concrete Demand} \times 380)/1000$
Coarse Aggregates Demand	Auxiliary	Ton	$(1000 \times \text{Concrete Demand})/1000$
Manufactured Sand Demand	Auxiliary	Ton	$(450 \times \text{Concrete Demand})/1000$
Concrete Supplied	Auxiliary	m^3	$\text{GB Cement Demand}/240 + \text{Water Demand}/165 + \text{Natural Sand Demand}/380$ $+ (\text{Coarse Aggregates Demand} - \text{Recycled Aggregates}/1000)$ $+ \text{Recycled Aggregates}/1000 + \text{Manufactured Sand Demand}/450$
Concrete Construction	Auxiliary	Ton	$\text{MIN}(\text{Concrete Demand}, \text{Concrete Supplied}) \times \text{Cubic Meter to Ton}$
Cubic Meter to Ton	Constant		2.235
Concrete Construction Stock	Level	Ton	Concrete Construction − Concrete Demolition
Concrete Demolition	Auxiliary	Ton	Concrete Construction × Demolition Rate
Demolition Rate	Auxiliary		0.457666×0.5
Concrete Waste	Auxiliary	Ton	Concrete Demolition + 1e-07 × Concrete Construction
Recycling Plant	Auxiliary	Ton	% Send to Recycle × Concrete Waste
Recycled Aggregates	Auxiliary	Ton	Recycling Plant × Recycling Rate
Recycling Rate	Constant		0.9
Gravel Extraction	Auxiliary	Ton	Manufactured Sand Demand + Coarse Aggregates Demand − Recycled Aggregates
Gravel Pit	Level	Ton	−Gravel Extraction
Recycle Factory Fee	Constant	$	80
Recycling Logistics Cost	Constant	$	445
Recycle Cost	Auxiliary	$	New Recycled Logistics Cost + Recycle Factory Fee
New Recycled Logistics Cost	Auxiliary	$	Recycling Logistics Cost + Additional Transportation Cost
Additional Transportation Cost	Auxiliary	$	(1 − % Send to Landfill) × 30
Landfill Fee	Constant	$	147
Landfill Cost	Auxiliary	$	Landfill Fee + Landfill Logistics Cost
Landfill Logistics Cost	Constant	$	450
Cost Different	Auxiliary	$	Recycle Cost − Landfill Cost
% Send to Landfill	Auxiliary		$1/(1 + \exp(-(1.5869 - (-0.0829612) \times \text{Cost Different})))$
% Send to Recycle	Auxiliary		1 − % Send to Landfill
Landfill	Auxiliary		Concrete Waste × % Send to Landfill + (1 − Recycling Rate) × Recycling Plant
Total Concrete Landfill	Level		Landfill

9.8 million tons of C&D waste in 2020–2021 [Australian Government Department of Climate Change and Water, 2022]. In formulating our model, we consulted recycling industry professionals who indicated that a well-designed recycling plant can achieve about a 90% recycling efficiency for incoming C&D waste. We further assumed that roughly 50% of the total C&D waste stream is composed of concrete waste. Using the modeled concrete construction activity as an index of overall construction activity, we derived the corresponding concrete demolition rate such that the model's annual concrete waste generation aligns with these figures. Specifically, the demolition rate was calibrated so that the amount of concrete waste produced in the model corresponds to 50% of the total C&D waste (9.8Mt), and this waste is processed with a 90% recycling efficiency under baseline conditions (as described next).

3.2.2.2 Sydney Concrete Recycling Choice Model

Figure 3.3 depicts the decision-making sub-model for how concrete waste is handled (recycling vs. landfill) in Sydney. In this component, we consider the total costs associated with recycling and landfilling, including both the processing fees and logistics (transportation) costs for each option. Based on industry input, we estimated baseline values for the recycling logistics cost (transportation cost to a recycling facility) and the landfill logistics cost (transportation cost to a landfill site). The parameters for Recycle Factory Fee ($80 per ton), Recycling Logistics Cost ($445 per ton), Landfill Fee ($147 per ton), and Landfill Logistics Cost ($450 per ton) used in this study are based on representative assumptions derived from consultations with local industry experts and available industry reports. It is important to note that these fees and costs can vary significantly across different locations within Sydney due to varying transport distances, local market conditions, facility capacities, and operational practices. These, combined with typical recycling facility fees and landfill tipping fees, yield a total recycling cost and a total landfill cost for a unit of waste. The decision of whether a demolition contractor chooses to recycle concrete waste or send it to landfill is modeled as a function of the difference between these two total costs.

According to national waste data, approximately 80% of C&D waste in Australia is directed to recycling, and about 90% of the waste that is sent to recycling facilities is successfully processed into recycled materials [Australian Government Department of

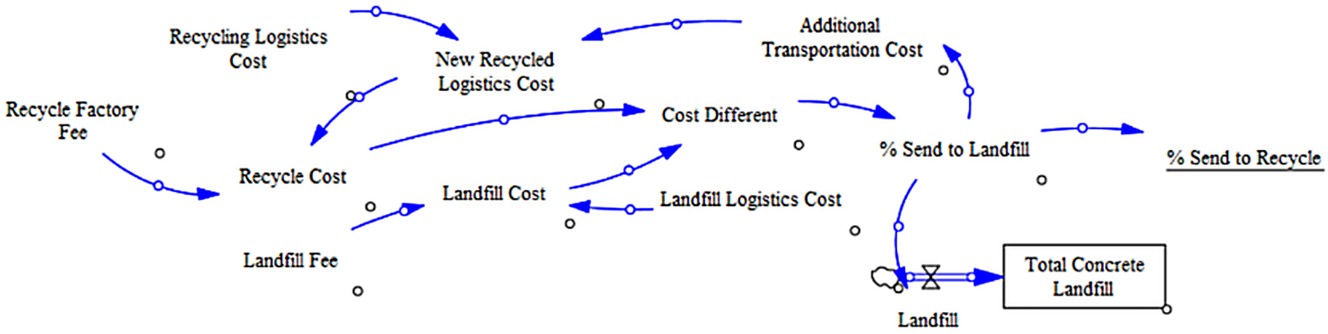


FIGURE 3.3. Sydney concrete recycling choice model

Climate Change and Water, 2022]. Applying these ratios, we estimate that roughly 89% of C&D waste (0.80/0.90 ≈ 0.89) is initially sent to recycling facilities, with the remaining 11% disposed in landfills, under current conditions. We assume that, in general, companies will choose the more economical disposal route. In other words, for about 11% of the waste, landfilling remains the cheaper option and thus is chosen. To represent this behavior in the model, we employed a binary logit choice function that determines the fraction of waste sent to landfill versus recycling based on the cost difference between the two options. The logistic function was calibrated so that at the baseline cost values (i.e., where the average total landfill cost is slightly lower than the total recycling cost), it reproduces this roughly 89% recycle vs. 11% landfill split observed in practice. The resulting function is:

$$\text{Waste Sent to Landfill \%} = \frac{1}{1 + \exp\Big[-\big(1.5869 + 0.0829612 \times \Delta\text{Cost}\big)\Big]}. \tag{3.1}$$

It is important to note that changes in one cost can influence the other indirectly through logistics behavior. For instance, if rising landfill fees prompt more companies to choose recycling (making landfilling less attractive economically), the average transportation distance for those companies might increase, since they forego nearby landfills in favor of more distant recycling facilities. In our model, this effect is captured by an additional transportation cost ($4.20/ton/km)term that increases as the fraction sent to recycling grows (reflecting the need to use longer routes when the nearest disposal site is bypassed). This means that an increase in landfill fees, while encouraging recycling, can inadvertently raise the average logistics cost for recycling routes. Such feedback ensures the model realistically accounts for the trade-off between disposal fees and transportation efficiency.

3.2.2.3 Integration of Sub-models and Gravel Extraction Calculation

Finally, we integrated the concrete production and recycling choice sub-models to capture the complete circular flow and its effects on natural resource extraction. As illustrated in Figure 3.4, recycled aggregate generated from the recycling choice sub-model directly feeds into the concrete production model. Concurrently, any aggregate demand not satisfied by recycled materials—specifically coarse aggregate and manufactured sand—necessitates virgin gravel extraction from gravel pits. In this study, we assume an initial total gravel pit resource of 100 million tons. Gravel extraction is thus calculated as the difference between the total aggregate required for concrete production and the available recycled aggregate. This integration enables the model to monitor depletion of the gravel resource stock over time, reflecting its non-renewable nature. Consequently, reductions in gravel extraction resulting from higher recycling rates directly extend gravel pit longevity. By connecting these sub-models, the approach allows comprehensive analysis of how varying waste management scenarios affect recycling performance, landfill volumes, and virgin material consumption.

3.2.3 Model Validation and Empirical Grounding

Although the system dynamics model is conceptual in structure, we undertook several steps to ensure empirical fidelity and practical relevance:

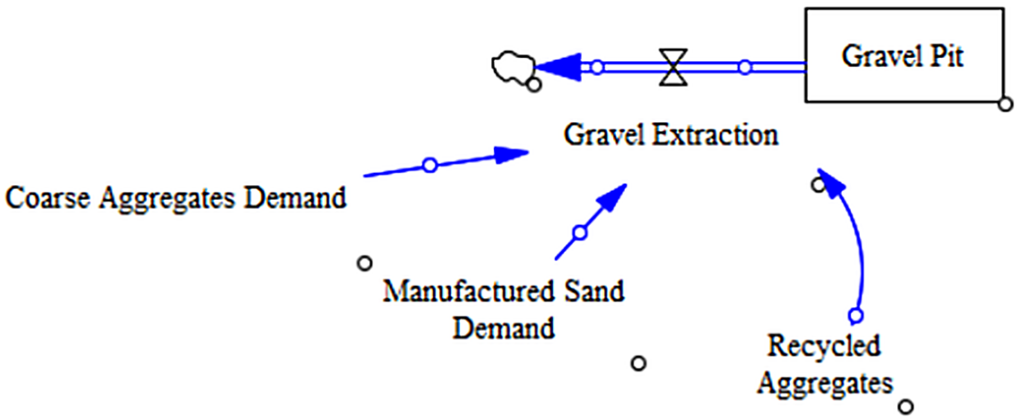


FIGURE 3.4. Gravel pit extraction

- **Data Calibration:** Key model parameters were derived from authoritative sources, including official C&D waste statistics from New South Wales (2020–2021), infrastructure usage reports, and detailed interviews with local recycling contractors and plant operators. This ensures that the model reflects actual material flows and economic structures observed in the Sydney metropolitan context.
- **Behavioral Realism:** The logit-based routing function was calibrated to match observed waste management behaviors, achieving an equilibrium where approximately 89% of waste is recycled—consistent with national C&D recycling performance data.
- **Face Validity via Stakeholder Review:** Model structures and simulation outputs were cross-validated through iterative consultation with industry stakeholders, providing qualitative feedback to align model assumptions with ground realities.
- **Scenario Realism:** Simulation scenarios were constructed using realistic ranges for landfill and recycling costs, informed by industry reports and local fee schedules. This ensures that policy insights derived from the model are implementable under plausible economic conditions.

3.3 Scenario Results and Discussion

In this section, we present the findings from our SD model simulations and discuss their implications. We first describe the scenario analysis approach, then detail the results showing how various cost changes affect recycling rates, landfill accumulation, and gravel extraction. Finally, we discuss the broader implications of these results for policy development and industry practices in the context of circular construction.

3.3.1 Scenario Analysis

After constructing and validating the SD model of Sydney's concrete supply chain, we conducted a series of scenario simulations to investigate the interrelationships between recycling costs, landfill costs, and logistics costs. The primary objective was to elucidate how changes in these economic factors, both individually and in combination, influence key outcomes such as the recycling rate, landfill rate, total landfill mass, and gravel extraction. We designed a range of scenarios by varying the logistics costs for recycling and landfilling around the baseline values. These scenarios included, for example, a 10% increase in the landfill logistics cost, a 10% increase in the recycling logistics cost, a 25% decrease in either the landfill or recycling logistics cost, as well as more extreme combined changes like a 50% decrease in both costs or a 100% increase in both. This set of scenarios provides a comprehensive examination of the system's sensitivity to cost fluctuations. Such cost changes can realistically occur due to policy interventions (e.g., higher landfill levies or new recycling subsidies) or market forces (e.g., changes in fuel prices affecting transport costs or adjustments in recycling facility fees). By exploring these what-if cases, we capture the complex interplay of economic and regulatory factors within the waste management system.

The outcomes of these scenarios at the end of the simulation period are summarized in Table 3.2 and 3.3. Each scenario represents a specific adjustment in recycling and/or landfill logistics costs, and the table records the resulting values of several pertinent metrics. The columns in Table 3.2 and 3.3 are defined as follows:

(1) **Scenario:** A brief description of the cost variation applied (e.g., "Landfill logistics cost +10%" or "Both costs −50%"), with a base case included for reference.

(2) **Recycling Cost:** The total recycling cost in that scenario (including recycling facility fee plus recycling logistics cost, in $ per ton). This reflects how changes in recycling practices or policies alter the cost structure for recycling concrete waste.

(3) **Landfill Cost:** The total landfill disposal cost in that scenario (including landfill tipping fee plus landfill logistics cost, in $ per ton). This shows the sensitivity of landfill expenses to changes in transport costs or fees.

(4) **Cost Difference:** The difference between the recycling cost and the landfill cost (Recycling minus Landfill, in $). This metric indicates the economic incentive or disincentive for choosing recycling over landfilling. A positive value means recycling is more expensive than landfilling (discouraging recycling), while a negative value means recycling is cheaper (encouraging recycling).

(5) **% Sent to Recycle:** The percentage of concrete waste directed to recycling facilities under the scenario. The logit choice model determines this and indicates how responsive the recycling uptake is to the cost difference.

(6) **% Sent to Landfill:** The percentage of concrete waste sent to landfills in the scenario. (Since all waste must go either to recycling or landfill, this value is essentially 100% minus the above recycling percentage.)

(7) **Total Landfill (Million tons):** The cumulative quantity of concrete waste (in million tons) that has been landfilled over the 120-time steps simulation. This provides a measure of long-term landfill burden under each scenario.

(8) **Total Landfill / Base:** The total landfilled waste normalized to the base scenario (unitless ratio). A value below 1 indicates less landfill accumulation than the baseline, while a value above 1 indicates more.

(9) **Gravel Pit Balance (Million tons):** The remaining gravel resource in pits at the end of the simulation. This reflects how much virgin gravel has been conserved or depleted relative to the initial amount, highlighting the linkage between recycling rates and the consumption of natural aggregates.

(10) **Total Gravel Extraction (Million tons):** The total amount of virgin gravel extracted over the 120 time steps. This is inversely related to the use of recycled aggregate—higher recycling of aggregate leads to lower gravel extraction.

(11) **Total Gravel Extraction / Base:** The gravel extraction amount normalized to the base scenario (unitless). This helps compare how each scenario increases or decreases the reliance on virgin materials relative to the baseline.

TABLE 3.2. Scenario comparison at time step 120 — cost inputs and routing shares

Scenarios	Recycling Cost ($/t)	Landfill Cost ($/t)	Recycling Rate (%)	Landfill Rate (%)
Landfill logistic +10%	445	495	99.60	0.40
Recycling logistic +10%	489.5	450	41.58	58.42
Landfill logistic –25%	445	337.5	0.70	99.30
Recycling logistic –25%	333.8	450	100.0	0.00
Both cost –50%	222.5	225	87.97	12.03
Both cost +100%	890	900	92.42	7.58
Base case	445	450	89.64	10.36

Table 3.3. Scenario comparison at time step 120 — landfill and gravel outcomes

Scenarios	Total Landfill (Mt)	Landfill vs. Base (ratio)	Gravel Pit Balance (Mt)	Gravel Ext. vs. Base (ratio)
Landfill logistic +10%	4.09	0.53	23.26	0.956
Recycling logistic +10%	24.78	3.23	2.56	1.213
Landfill logistic –25%	39.35	5.14	–12.00	1.394
Recycling logistic –25%	4.09	0.53	23.38	0.954
Both cost –50%	8.25	1.08	19.09	1.007
Both cost +100%	6.66	0.87	20.68	0.988
Base case	7.66	1.00	19.68	1.000

3.3.2 Results

To ensure the credibility of the results, all simulations are grounded in empirically derived parameters and validated behavioral assumptions. The cost structures, routing shares, and recycling efficiencies used in the scenarios closely mirror those observed in practice. This empirical foundation strengthens the model's value as a decision-support tool, enabling policymakers and stakeholders to explore the likely consequences of changes in fees, subsidies, and logistics strategies within a realistic operational framework. The simulations reveal significant economic and environmental impacts stemming from changes in recycling and landfill logistics costs. Below, we detail the results for the various scenarios, grouped by the type of cost variation.

3.3.2.1 Effects of Recycling and Landfill Cost Changes

Individual cost variations. Adjusting the landfill logistics cost has a dramatic effect on waste management outcomes. For instance, a 10% increase in the landfill logistics cost (from the baseline \$ 450 to \$ 495 per ton) causes the vast majority of concrete waste to be recycled, with 99.6% of material being diverted from landfill. In this scenario, the total concrete waste sent to landfill over 120 time steps drops to only about 4.09 million tons, and the cumulative gravel extraction is reduced to approximately 76.74 million tons (since more recycled aggregate is available to replace virgin aggregate). Conversely, a 25% decrease in the landfill logistics cost (to $ 337.5) makes landfilling far more attractive economically, resulting in a recycling rate of only about 0.7%. In that case, virtually all waste goes to landfill, leading to about 39.35 million tons of landfill accumulation and a corresponding increase in total gravel extraction to roughly 112 million tons (as recycled aggregate supply plummets when recycling is not utilized).

Changes in the recycling logistics cost exhibit an analogous influence in the opposite direction. A 10% increase in the recycling logistics cost (from $445 to roughly $489.5) significantly suppresses recycling activity and only about 41.6% of the waste is recycled under this scenario. Consequently, the landfill accumulation rises to 24.78 million tons, and total gravel extraction increases to around 97.44 million tons, compared to the baseline. In contrast, making recycling logistics more economical greatly boosts recycling. For example, a 25% reduction in the recycling logistics cost (to about $333.8) yields an almost complete shift to recycling—nearly all waste is recycled in this scenario, with only 3.96 million tons ending up in landfills. Such a scenario of very low recycling cost results in a substantial decrease in landfill burden (around half of the base case landfill mass) and a corresponding reduction in the need for virgin gravel extraction.

Combined cost variations. When both recycling and landfill costs are altered simultaneously, the outcomes depend on the balance of those changes. If both logistics costs are reduced by 50%, the recycling rate remains high but actually dips slightly to about 87.97% (compared to 89.64% in the base case). In this scenario, because landfilling has also become much cheaper, some waste that would have been recycled in the base case is now landfilled despite the lower recycling cost. This leads to a total landfill mass of about 8.25 million tons over 120 time steps (higher than the 7.66 million tons in the base case) and a slight increase in gravel extraction due to the marginally lower use of recycled aggregate. In the opposite extreme, a simultaneous 100% increase in both landfill and recycling logistics costs (doubling each to very high levels) pushes the recycling rate up to roughly 92.42%. Here, although recycling has become more costly, landfilling has become prohibitively expensive, resulting in more waste being recycled than in the base case. The total landfill accumulation in this scenario falls to about 6.66 million tons (slightly below the base case), and the total gravel extraction is about 1% less than in the base scenario. These combined scenarios underscore a somewhat counter-intuitive result of uniformly lowering all disposal-related costs can reduce the incentive to recycle (since landfilling also becomes cheap), whereas uniformly raising costs penalizes landfilling more and thus can actually improve recycling rates and conservation of virgin materials.

Figure 3.5 provides a time-series comparison of the total concrete landfill mass under select scenarios against the base case. The base case (no cost change) results in 7.66 million tons of concrete in landfills over the 10-year period. The trajectory shifts notably under different cost conditions: for example, the scenario with both recycling and landfill costs doubled yields a slightly lower landfill curve, ending at 6.66 million, whereas halving both costs produces a higher curve ending at 8.25 million. The scenarios with one cost changed and not the other show even more pronounced deviations—most notably, the landfill logistics cost reduction scenario increase the landfill accumulation to over 39 million tons, while the recycling cost reduction scenario drives it down to under 4 million tons. These results highlight how sensitive landfill outcomes are to the relative economics of recycling vs. disposal. In summary, making recycling financially attractive (either by raising landfill costs or lowering recycling costs) can drastically reduce landfill use, whereas making landfilling cheaper has the opposite effect, even if recycling costs also drop.

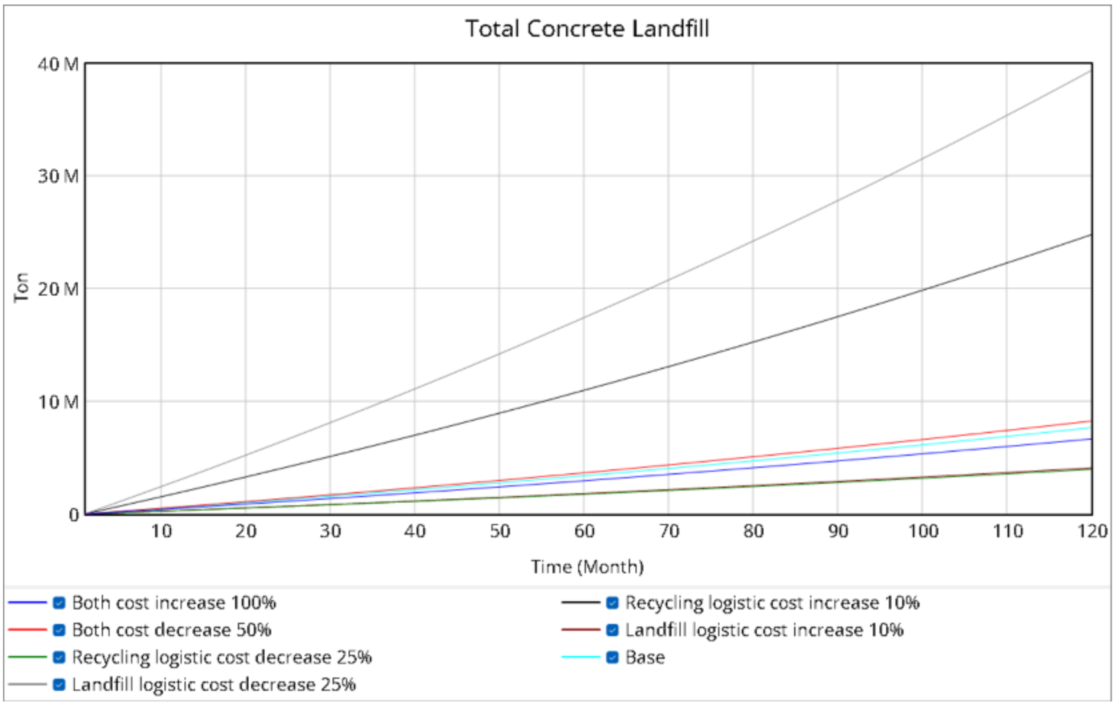


FIGURE 3.5. Total Concrete Landfill under different scenarios

As shown in Figure 3.6, the knock-on effect of reducing landfill waste is a decrease in the demand for new gravel from pits, but this effect is less dramatic than the changes in landfill mass. In our model, concrete aggregate is only one of several uses for gravel, meaning that even if all concrete waste is recycled, there is still ongoing gravel extraction for other purposes (or to make up other parts of the concrete mix). Thus, while higher recycling rates do lead to lower gravel extraction, the reduction in gravel demand is moderate in comparison to the large swings in landfill usage. For instance, the scenario that nearly eliminates concrete landfilling (recycling logistics cost −25%) still requires some gravel extraction because recycled aggregate replaces only the coarse aggregate portion of new concrete, and other constituents (like sand or other aggregate uses outside concrete production) continue to draw on natural resources. Nonetheless, every increase in recycling does correspond to some savings in gravel: the scenario with the highest recycling (and lowest landfill) shows the least gravel extracted, whereas the scenario with massive landfilling draws heavily on gravel pits.

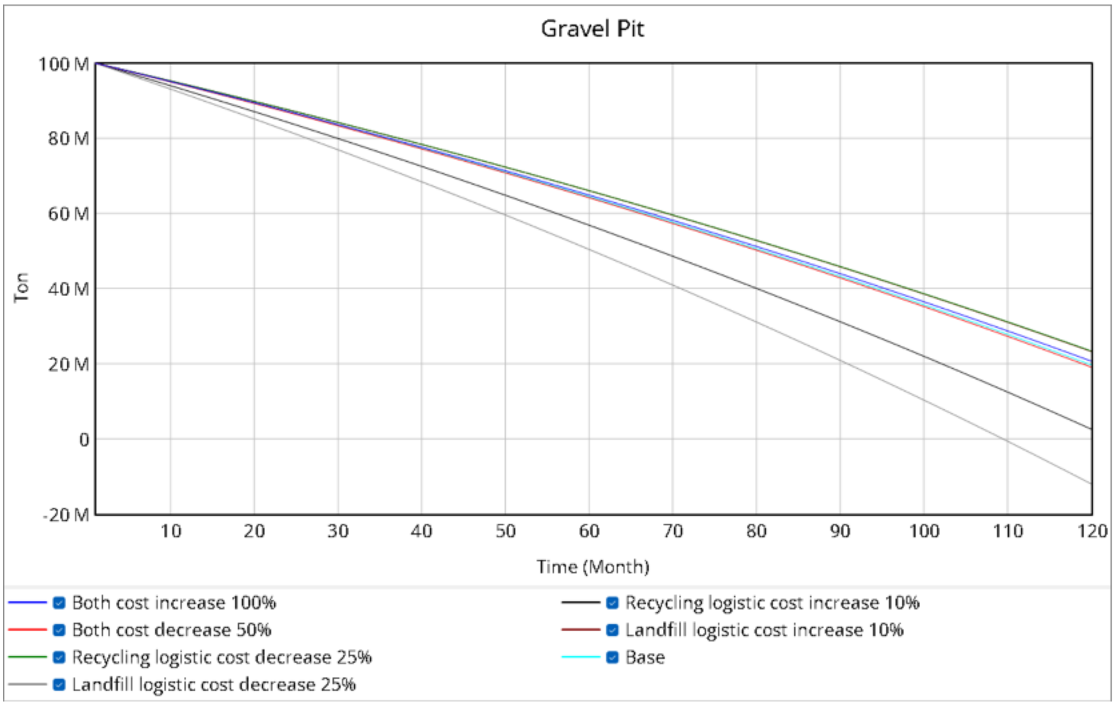


Figure 3.6. Gravel Pit remain

The above findings confirm that the model behaves in line with real-world expectations that increasing the relative cost of a waste management route tends to discourage its use. When recycling becomes cheaper (or landfills become more expensive), recycling rates climb and landfill use drops, and vice versa. Importantly, these results underscore the necessity of maintaining an optimal cost ratio between recycling and landfill options to achieve desirable outcomes—high recycling rates and minimal gravel extraction. Our analysis suggests that careful management of the balance between recycling costs and landfill costs can effectively serve as a lever to counteract inefficiencies in logistics. Even in situations where logistics costs are inherently high (for example, if transport distances are large or fuel prices surge), a well-chosen differential between landfill fees and recycling incentives can still yield high recycling uptake. In practice, this means that strategic financial planning—such as adjusting fees, subsidies, or taxes in the waste disposal system—can mitigate operational inefficiencies and ensure that sustainability goals are met. For instance, if geographical constraints make transportation costly, policymakers could increase landfill levies or provide recycling subsidies to tilt the cost ratio in favor of recycling, thereby overcoming the logistics disadvantage. In summary, managing the economic balance between recycling and landfilling emerges as a crucial strategy for promoting sustainable practices in circular construction and concrete waste management.

3.3.2.2 Impacts of Logistics Costs on Recycling, Landfilling, and Gravel Extraction

In addition to the scenario end-point comparisons above, our model results provide insight into the continuous relationships between cost variables and system outcomes. Figures 3.7–3.9 illustrate these relationships by varying one cost factor while holding others constant.

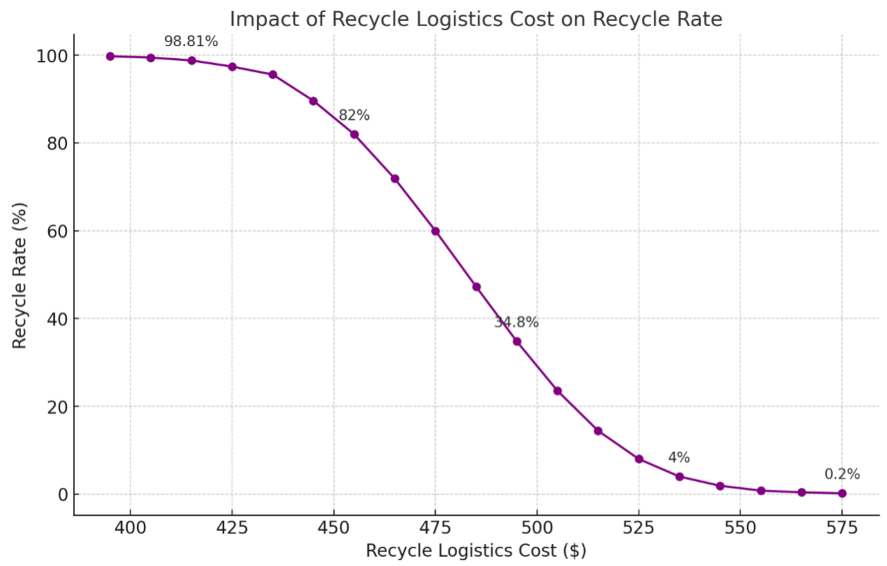


FIGURE 3.7. Impact of Recycle Logistics Cost on Recycle Rate

Figures 3.7–3.9 further illustrate the continuous, non-linear relationships between logistics costs and system behavior.

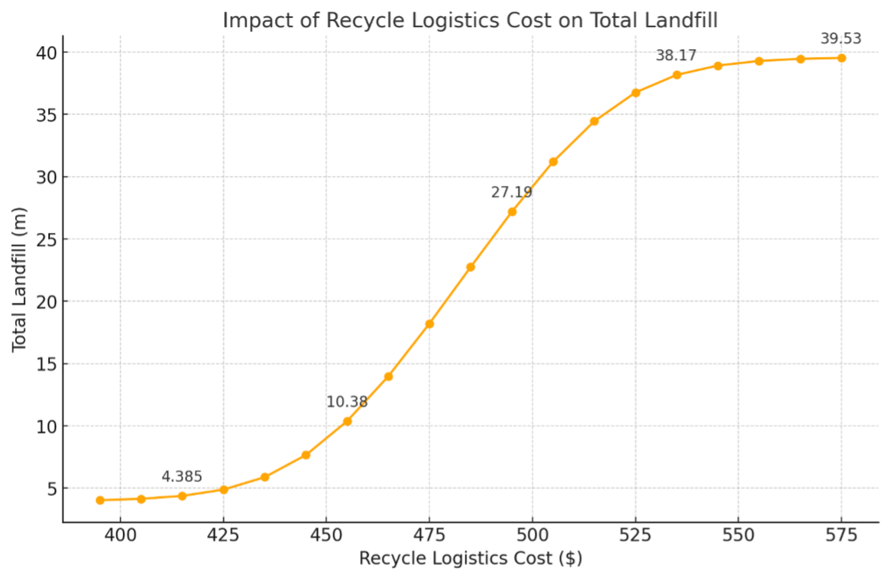


Figure 3.8. Impact of Recycle Logistics Cost on Total Landfill

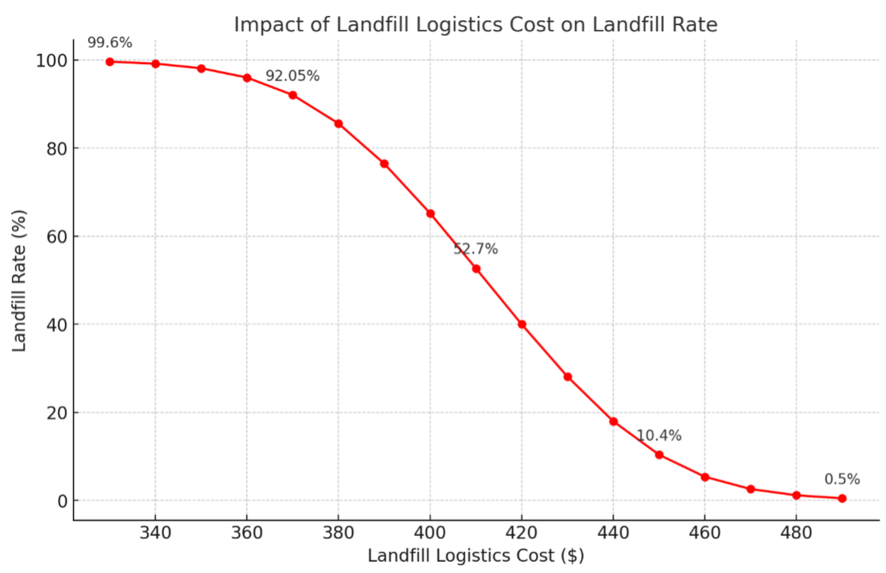


Figure 3.9. Impact of Landfill logistics cost on Landfill Rate

As recycling logistics cost decreases, the recycling rate follows an S-shaped curve—remaining minimal above $550, but surpassing 90% when cost falls below $400. A critical tipping point lies near \$485, beyond which recycling sharply accelerates. Correspondingly, landfill volume plummets from over 39 Mt to under 4 Mt as recycling becomes cheaper.

The landfill rate exhibits an inverse pattern with respect to landfill logistics cost. When landfill transport cost is high (e.g., \$490), nearly all waste is recycled. However, lowering this cost below \$400 rapidly increases landfill dependence, with almost full landfilling occurring at \$330.

These relationships confirm the model's behavioral validity: disposal decisions are highly cost-sensitive, and tipping points amplify the policy impact of even modest cost shifts. Strategically adjusting either landfill fees or recycling subsidies can drive the system toward sustainable outcomes, provided the cost differential remains favorable to recycling.

3.3.3 Discussion and Implications

The system dynamics modeling results reveal key nonlinear behaviors in the concrete recycling system, offering several insights for policy and practice. Most notably, we identify a strongly nonlinear relationship between cost variables and recycling or landfilling outcomes. Unlike linear assumptions in simpler models, our findings suggest that marginal changes in cost can trigger disproportionately large shifts—sometimes exponential—in system behavior. This highlights the potential for tipping points, where a critical cost differential can rapidly accelerate recycling rates. Recognizing and targeting such thresholds can inform more effective pricing strategies, such as landfill levies or recycling subsidies.

A second key insight is the importance of maintaining an optimal cost ratio between recycling and landfill disposal. The model shows that recycling can be maximized without excessive overall costs if this balance is carefully managed. Policymakers can use this information to calibrate economic levers—subsidies, fees, or taxes—so contractors are nudged toward recycling, even under varying market or operational conditions. These relationships are suitable for integration into decision-support tools, helping waste authorities predict how pricing changes will affect recycling uptake.

Beyond costs, logistics inefficiencies—such as long transport distances or outdated vehicle fleets—play a critical role. Our model shows that well-calibrated economic incentives can mitigate these inefficiencies, allowing high recycling rates even under suboptimal conditions. In the short-to-medium term, such incentives can offset logistics constraints, while infrastructure upgrades may gradually reduce the need for them.

However, policy changes must consider system-wide ripple effects. For instance, increasing landfill fees may unintentionally shift waste to distant recycling sites, thereby raising transport-related emissions. This calls for complementary measures—such as improved siting of recycling facilities and enhanced transport infrastructure—to ensure sustainability gains are not offset by logistical burdens.

Our modeling scope focuses on current industry norms, particularly the use of recycled aggregates in low-strength concrete. Yet the framework is adaptable as it can accommodate future shifts such as expanded use of recycled materials in high-strength applications. This flexibility makes the model a valuable tool for exploring long-term scenarios, including those driven by technological innovation or regulatory changes.

Future research could focus on optimizing logistics in tandem with economic incentives. For example, integrating route optimization tools or improving fleet efficiency could reduce transport costs and enhance the cost-effectiveness of recycling. Similarly, innovations that lower recycling process costs—whether through technology, centralized processing, or new business models—could reinforce the economic viability of circular practices.

In sum, this study advances a more integrated understanding of cost, logistics, and technology in circular construction. It offers actionable insights for designing effective, adaptive policies and underscores the importance of aligning economic instruments with infrastructure and operational strategies. Such alignment is critical for achieving a sustainable, circular economy in the construction sector.

3.4 Limitations and Future Research

This study, while offering new quantitative insight into concrete-recycling dynamics, is subject to several limitations. First, key inputs—such as contractors' price elasticities and average haul distances—were derived from a limited set of industry interviews and secondary reports; richer, project-level data would sharpen numerical estimates of tipping points. Second, the model is calibrated exclusively for the Sydney metropolitan area, and its transferability to regions with different regulatory regimes, infrastructure layouts, or market structures remains untested. Third, we focused on a representative N20 concrete mix and excluded other demolition materials and high-strength concrete applications, thereby abstracting from possible interactions in mixed-waste streams. Fourth, landfill levies and recycling fees were treated as exogenous and time-invariant, whereas real-world policy instruments evolve and may respond endogenously to market conditions. Finally, our assessment is restricted to material-flow and resource-extraction outcomes; life-cycle carbon emissions associated with transport and processing were not quantified.

Future work can address these gaps in several ways. Integrating high-resolution transport-cost datasets, time-series waste statistics, and spatially explicit demolition logs would improve calibration and validate the robustness of cost thresholds. Applying the framework to other jurisdictions—such as Melbourne, Auckland, or Singapore—would facilitate cross-regional comparison and test the model's generalisability. Coupling the system-dynamics core with GIS-based facility-siting and vehicle-routing optimisation could reveal how spatial reconfiguration of recycling infrastructure alters both economic and environmental outcomes. Incorporating agent-based or discrete-choice modules would capture behavioural heterogeneity among contractors, while embedding life-cycle carbon accounting would allow joint evaluation of cost, material-flow, and climate impacts. Finally, extending the material scope to multi-material C&D streams and to high-strength recycled-aggregate concrete would present a more holistic picture of circular-construction strategies. Collectively, these avenues promise to enhance the predictive accuracy and policy relevance of the model, advancing efforts to achieve a fully circular construction economy.

3.5 Conclusion

This work developed a calibrated *system-dynamics* model to examine how economic and logistical cost structures determine the fate of concrete demolition waste in Sydney's construction sector. Three core insights emerge:

1. **Cost tipping points.** A 10 % increase in landfill-logistics costs or a 25 % decrease in recycling-logistics costs diverts more than 95 % of concrete waste to recycling, cutting cumulative landfill mass by almost one-half and lowering virgin-gravel extraction by 5 % to 6 %.
2. **Leverage for policy and industry.** Aligning landfill levies, recycling subsidies, and facility-siting decisions with these thresholds offers a near-term, evidence-based pathway to accelerate circular-construction goals without large infrastructure outlays.
3. **Robustness and limitations.** While qualitative patterns are stable, absolute magnitudes depend on spatial variability in transport distances and on contractors' price responsiveness; parameter refinement remains a priority.

In the Practical implications, the model furnishes a decision-support tool for (i) policy-makers to set cost differentials that nudge behaviour toward recycling and (ii) firms to prioritise investments in transport optimisation and recycled-aggregate supply chains. While the system dynamics framework developed in this study is broadly adaptable, we caution that the specific numerical thresholds and behavioral assumptions are calibrated to the Sydney context. The effectiveness of landfill levies or recycling subsidies, for example, may vary significantly in regions with different cultural norms, legal structures, infrastructure maturity, or economic constraints. Thus, direct policy transferability is limited without local recalibration. We recommend that future applications of the model in other jurisdictions incorporate region-specific data and engage local stakeholders to account for socio-institutional variations in waste management behavior and regulatory enforcement. Further work can involve extending the framework with geospatial optimization, heterogeneous behavioral modules, and life-cycle carbon accounting, which will sharpen its predictive accuracy and widen its applicability to multi-material demolition streams and other metropolitan contexts. In summary, the study demonstrates that modest, well-targeted fiscal measures can overcome logistical frictions, substantially reduce landfill dependency, and conserve finite resources—thereby advancing the construction sector toward a genuinely circular economy.

Chapter 4

System Dynamics Analysis of Concrete Recycling and Waste Management in Circular Construction: A Case Study of Sydney's Construction Sector

4.1 Introduction

The construction industry, a central pillar of global economic development, is a significant contributor to global emissions, accounting for approximately 40% of energy-related carbon emissions [Programme, 2021]. This impact is expected to increase further due to the projected growth in the global middle-income population [Norouzi et al., 2021], escalating construction demands worldwide. Consequently, nations must implement strategies to reduce the carbon footprint within the construction industry. Growing environmental concerns have led to a paradigm shift in the construction industry [Lee et al., 2010, Liberalesso et al., 2020]. This shift is evidenced by a heightened focus on green construction methods, for example, the use of eco-friendly materials [Pacheco-Torgal, 2014, Robayo-Salazar et al., 2023], energy-efficient building designs [Gauch et al., 2023, Ibrahim et al., 2023, Han et al., 2020], and a concerted effort to reduce the carbon footprint and waste [Guo and Chuai, 2023, Maraqa et al., 2023, Karamoozian et al., 2023, Montalbán-Domingo et al., 2023]. As a result, the number of countries with declared net-zero emission goals has risen from 124 in late 2020 to 149 in 2023 [Jordans, 2023]. The corporate sector has mirrored this trend, with the count of publicly listed companies pledging net-zero emissions increasing from 417 to 929 [Jordans, 2023]. Despite these advances, several countries have reported delays or reductions in their planned carbon reduction targets [BBC News, 2023, Will, 2023]. Government intervention, particularly through targeted policies and regulatory frameworks, significantly influences the development of public-private partnerships in advancing green construction practices [Sun et al., 2023, Nigra and Bossink, 2023]. Green subsidies and green taxes are two common policy tools employed by governments to shape environmental strategies [Bai et al., 2023, Gao et al., 2018]. However, the lack of enforcement policies and the higher costs associated with green products hinder the adoption of circular construction practices. Additionally, a lack of public awareness about the benefits of green products contributes to the preference for conventional products [Liu et al., 2023, Qiao et al., 2022].

Despite extensive research on green construction, significant gaps remain in our understanding of stakeholder dynamics and policy effectiveness in this sector. Previous studies have primarily focused on either the economic aspects or technical elements of green construction, often neglecting the complex interplay between different stakeholders and the long-term impacts of policies. For instance, while the influence of green taxes on system evolution has been established, there is limited understanding of how the effectiveness of these taxes evolves over time, particularly regarding their differential impacts on developers versus customers. Furthermore, existing research often fails to capture the dynamic and fluid nature of interactions between government bodies, businesses, and consumers in the green construction sector. Although recent years have seen the application of mathematical frameworks used to examine stakeholder behaviors in construction [Chen et al., 2021], these models typically do not fully encompass the ongoing changes characteristic of these interactions.

To address these research gaps, our study employs a novel combination of evolutionary game theory and system dynamics to analyze the adoption of green products in the construction industry. This integrated approach allows us to model the complex interactions between stakeholders over time, incorporate dynamic policy variables, and analyze the combined effects of multiple policy interventions. By doing so, we aim to provide a more comprehensive and realistic representation of the evolving dynamics in the green construction sector. The primary objectives of this research are to identify the stable equilibrium states required for green construction practices and determine the specific conditions that lead to a green transition. We aim to analyze how stakeholders' strategic choices and other relevant factors contribute to the evolution of these equilibrium states. Furthermore, we examined the differential impacts of green tax policies, changing public awareness, and green finance on developers and customers. To achieve these objectives, we develop a tripartite evolutionary game model to investigate the factors influencing the strategy choices of each stakeholder group. We determine the payoff functions for each condition with all stakeholders and calculate the evolutionarily stable strategies for the government, developers, and customers using replicator dynamic equations. Following this, we derive the stability conditions based on Lyapunov stability theory [Lyapunov, 1992]. A system dynamics model is also developed to illustrate the interconnections among variables affecting the decision-making processes of the three stakeholders. Various scenarios and policies are evaluated, including different levels of green tax on customers and developers, dynamic green public awareness, and green credit from financial institutions to developers. Moreover, a comprehensive scenario policy combination assesses the simultaneous implementation of multiple policies. Each scenario is analyzed by simulating the model with the respective policy adjustments and observing the resulting behaviors of stakeholders over time, focusing on their impact on the adoption of green practices.

This comprehensive approach enables us to examine the intricate relationships between government policies, market dynamics, and stakeholder behaviors in the green construction sector. Our research significantly extends prior work in green construction policy and modeling. First, we address the challenge of high tax rates potentially discouraging market participation [Sun et al., 2023] by introducing a dynamic taxation strategy. This approach, which starts with a low tax rate that gradually increases over time, builds upon the findings of Qiao et al. [2022] and Liu et al. [2023], acknowledging the adverse impacts of static, high-rate taxation on market stability. Second, we expand on Jiang et al. [2022] by exploring the government's ability to flexibly combine diverse policy measures and their effects on previously neglected stakeholders. This approach provides deeper insights into how such strategies drive the green transition. Lastly, our study integrates multiple policy mechanisms, including green financing [Deb et al., 2023], demonstrating how these factors synergistically amplify the effectiveness of sustainable construction policies. This research addresses a key limitation of earlier studies, which primarily examined isolated policy interventions, offering actionable recommendations for dynamically adjusting policies to ensure market stability, reduce costs, and achieve environmental goals. These findings support policymakers in crafting balanced strategies that align economic and environmental priorities.

The contributions of this research to the domain of green construction are multifaceted:

- **Policy Contributions:** This study highlights the effectiveness of dynamic taxation strategies, public awareness campaigns, and green financing as integrated policy tools. By demonstrating the benefits of combining these approaches, it underscores their critical role in accelerating stakeholder adoption of green practices and achieving sustainable transitions.
- **Practical and Theoretical Contributions:** The research provides tailored strategies for governments, developers, and customers, promoting gradual adaptation and stakeholder-specific interventions. It advances the theoretical understanding of dynamic interactions among stakeholders under varying policy conditions and emphasizes the importance of multi-policy interactions in fostering sustainable practices.
- **Methodological Contributions:** A novel framework combining evolutionary game theory and system dynamics modeling enables the analysis of complex,

time-dependent stakeholder behaviors. Rigorous validation through simulations and stability analysis ensures the robustness and reliability of the findings, offering a comprehensive tool for evaluating policy impacts.

The remainder of this paper is structured as follows: Section 4.2 provides a comprehensive summary of existing research related to green construction, focusing on carbon and green taxation, the application of evolutionary game theory and system dynamics, and the identification of current research gaps. Section 4.3 outlines the research framework and methodology, detailing the development of the tripartite evolutionary game model and the system dynamics model. Section 4.4 discusses the results of numerical simulations and scenario analyses, which evaluate the impact of various policy scenarios on stakeholder behaviors and the adoption of green construction practices. Section 4.5 explores the implications of these findings for policy-making and sustainable construction practices, while Section 4.6 concludes with a summary of the study's key contributions, its limitations, and recommendations for future research.

4.2 Literature review

4.2.1 The application of carbon/green tax in green construction

The concept of green construction emerged as a response to the environmental challenges posed by increasing global industrialization and urbanization, which have led to significant non-renewable energy consumption and greenhouse gas emissions [Lee et al., 2010, Liberalesso et al., 2020]. This approach aims to mitigate environmental impact by promoting energy efficiency, resource conservation, and the use of sustainable materials [Kats, 2003, Kibert, 2007, Luo et al., 2022]. National and international policies have played a crucial role in promoting green construction practices [Shafique and Mollaoglu, 2022]. Many countries have implemented policies and roadmaps aimed at achieving carbon neutrality in the building sector. These policies often emphasize the use of sustainable materials [Pacheco-Torgal, 2014, Robayo-Salazar et al., 2023], energy-efficient building designs [Gauch et al., 2023, Ibrahim et al., 2023], and efforts to reduce carbon footprints and waste [Guo and Chuai, 2023, Maraqa et al., 2023]. Among these policy strategies, taxation has emerged as one of the most widely used approaches, with carbon or green taxes being particularly prevalent. The implementation of carbon taxes imposes financial costs on greenhouse gas emissions, thereby incentivizing industries to reduce their carbon footprint and adopt more sustainable practices [Tsai et al., 2017]. Multiple studies have demonstrated the effectiveness of carbon tax policies in raising public awareness and positively impacting environmental behavior [Lu et al., 2013, Song et al., 2020, Sun et al., 2023]. However, the relationship between environmental regulations and economic considerations is complex. Sun et al. [2023] investigated how stringent environmental regulations can elevate costs and potentially influence investor sentiment and market participation. However, their study did not provide a comprehensive solution for balancing environmental goals with investment incentives, a crucial aspect in promoting sustainable construction practices. On the other hand, Qiao et al. [2022] and Liu et al. [2023] confirmed that government guidance and green taxes significantly influence the speed and outcome of system evolution in the green transition. However, these studies did not address the potential issue of high taxes discouraging market activities, a crucial consideration in policy implementation. In the realm of green financing, Deb et al. [2023] demonstrated that it can promote environmentally friendly and socially responsible practices in companies; however, the study did not offer a broader perspective on how multiple factors, including green financing, can combine with other policies to promote green construction practices. Jiang et al. [2022] acknowledged the need for flexible and adaptive policy approaches in promoting green practices. However, their study was limited in considering the government's flexible adoption of different policy combinations or novel measures in promoting green practices.

4.2.2 Research on the construction industry using evolutionary game theory

Evolutionary game theory has gained significant traction in construction industry research due to its efficacy in analyzing complex dynamics. Researchers found that increasing government subsidies does not necessarily enhance the likelihood of construction units adopting environmentally friendly practices. Instead, factors such as the income of construction units significantly influence their decision to pursue green building projects [Li et al., 2022b]. This finding underscores the importance of considering customer demand in promoting sustainable construction. For instance, Chen et al. [2018] demonstrated that in the recycling industry, cooperation and information sharing among companies are crucial for equitable construction waste disposal. Similarly, by looking at government, contractors, and recycling plants, Yuan et al. [2020] used this method to investigate the promotion of prefabricated residential buildings in China, finding that while the government initially leads the industry, the requirement for intervention diminishes as the industry evolves. Additionally, Chen et al. [2021] employed evolutionary game theory to examine the impact of government policies on green building technology adoption, concluding that government subsidies significantly encourage adoption. On the other hand, Chen et al. [2018] utilized evolutionary game theory to investigate the decision-making processes of construction contractors and government bodies in addressing illegal dumping and promoting recycling. Their research identified key influencing factors and posited that while increasing penalties may not effectively curb illegal dumping, enhancing public participation in monitoring could be beneficial.

4.2.3 Research on the construction industry using system dynamics

To understand the construction industry's contribution to carbon emissions, Li et al. [2021] employed system dynamics modeling to assess the impact of various parameters on the construction industry's carbon emissions and to forecast future emission trends. Zhang et al. [2024] advocate the use of system dynamics for analyzing and reducing emissions, highlighting the critical need for well-crafted policy development and implementation to prevent unforeseen consequences. In a similar vein, Porwal et al. [2023] successfully combined building information modeling (BIM) with system dynamics to minimize construction waste by changing project scope. They found that coordinated BIM design activities in the early planning stages, along with a commitment to reducing waste, are crucial. Adding to this, the work of Jiang et al. [2022] examines how factors like economic growth and carbon reduction technologies affect the carbon emissions of China's construction sector. They underscore the effectiveness of promoting carbon reduction technologies in decreasing emissions and suggest that policy support for low-carbon technologies is essential to meet carbon reduction goals.

4.3 Methodology

The notations used in this section are presented in Table A.1

we provide the initial parameter settings in Table 4.2, which were previously introduced in the Section System Dynamics Model Establishment.

4.3.1 Parameter Justification

Our model parameters come from three sources: published research, industry consultation, and reasonable assumptions where data is limited.

TABLE 4.1. Notation

Symbol	Description
G	Social utility benefit when the government applies a green tax.
C_3	Management cost when the government applies a green tax.
T	Environmental cost when customer and developer do not cooperate greenly.
S_1	Environmental and utility benefit when the customer chooses green.
S_2	Environmental and utility benefit when the developer chooses green.
P_2	Tax/penalty when the developer does not choose green.
P_1	Tax/penalty when the customer does not choose green.
U	Utility benefit for purchasing a product.
β	Degree of green (product greenness).
α	Extra utility received from the degree of green when buying green.
R	Utility gain when buying green.
C_1	Additional cost to the customer when buying green.
D	Social and utility benefit when the developer builds green.
F	Social cost when the developer does not build green.
θ	Cost transformation rate (from developer to customer).
V	Benefit for the producer when the product is sold.
C_2	Cost of a 'normal build'.
B	Producer's extra benefit when producing green.
E	Producer's loss when they do not meet green demand.
γ	Green credit from the bank when building green (operation cost reduction).

TABLE 4.2. Parameters used for simulation. Sources: Literature-based (*), Industry consultation (†), Assumption-based (‡).

Parameters	Value	Unit
G‡	400	$\$/m^2$
C_3†	100	$\$/m^2$
P_1†	150	$\$/m^2$
P_2†	150	$\$/m^2$
β‡	0.05	Ratio
α‡	0.8	Ratio
R*	230	$\$/m^2$
C_1*	250	$\$/m^2$
θ*	0.7	Ratio
C_2*	2950	$\$/m^2$
B†	100	$\$/m^2$
E‡	1000	$\$/m^2$
γ†	0.05	Ratio

4.3.1.1 Literature-Based Parameters

These values are grounded in existing studies:

- **Green product utility** ($R = \$230$): From Royne et al. [2011] on consumer willingness to pay for green building products
- **Green product premium** ($C_1 = \$250$): Based on Manso et al. [2021] documenting typical 10-15% price premiums
- **Construction costs** ($C_2 = \$2950$): Sydney construction cost data
- **Cost pass-through rate** ($\theta = 0.7$): Industry practice from Li et al. [2022b]

4.3.1.2 Industry Consultation

We obtained these through expert interviews and market analysis:

- **Tax rates** ($P_1, P_2 = \$150$): Based on carbon pricing in similar jurisdictions and consultation with 5 industry experts
- **Management costs** ($C_3 = \$100$): NSW EPA administrative cost estimates
- **Green financing** ($\gamma = 0.05$): Current rates from major Australian banks

4.3.1.3 Assumptions

Where empirical data is unavailable, we made reasonable assumptions:

- **Social benefits** ($G = \$400$): Estimated environmental externality value
- **Greenness factor** ($\beta = 0.05$): Modest environmental improvement level
- **Demand penalty** ($E = \$1000$): Opportunity cost of missing green market demand

All parameters were tested for sensitivity and adjusted to ensure the model reaches stable, realistic outcomes. We acknowledge that some values rely on assumptions and recommend future empirical validation.

4.3.2 Research framework

This study integrates evolutionary game theory (EGT) and system dynamics (SD) to overcome the limitations of using either method alone. EGT identifies stable equilibria but assumes static conditions, while SD captures dynamics but lacks strategic interaction modeling.

4.3.2.1 Mathematical Integration

The integration occurs through replicator dynamic equations, which serve as the bridge between methodologies:

EGT Foundation: Identifies equilibrium points and stability conditions using Jacobian analysis (Table 4.3)

SD Implementation: Converts replicator equations (4.12-4.14) into stock-and-flow structures where:

- Stakeholder strategy probabilities (x, y, z) become stock variables
- Payoff differences $(U_{i1} - U_{i2})$ become rate equations governing probability changes
- Policy parameters can vary dynamically over time

4.3.2.2 Dynamic Policy Analysis

The integrated framework uniquely enables analysis of time-varying policies:

$$P_1(t) = P_{1,base} + k_1 \cdot t \quad \text{(Dynamic taxation)} \tag{4.1}$$

$$R(t) = R_{base} \cdot (1 + k_R \cdot t) \quad \text{(Evolving awareness)} \tag{4.2}$$

This integration provides strategic rigor from EGT with temporal realism from SD, enabling comprehensive policy evaluation that neither method achieves independently.

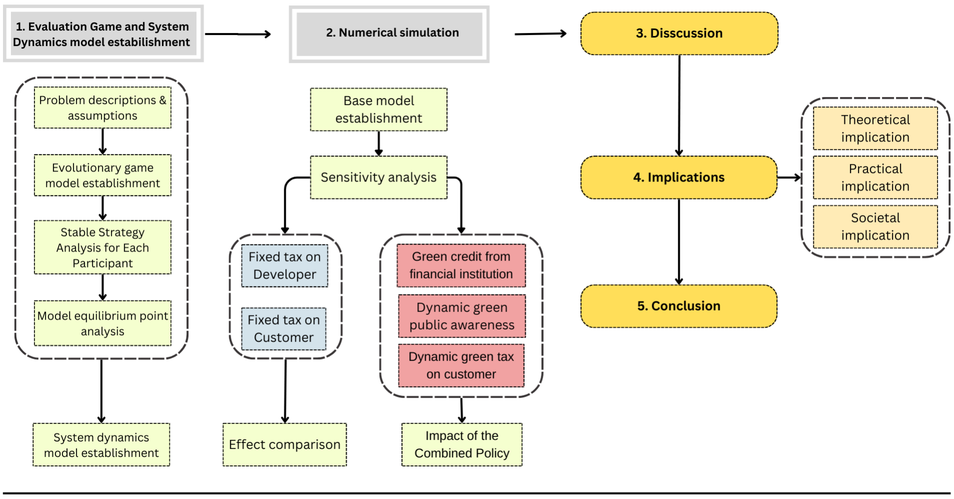


FIGURE 4.1. Research framework

As shown in Fig. 4.1, this research employs an integrated approach that combines Evolutionary Game Theory with System Dynamics to analyze the adoption of green construction practices within the construction industry. The framework is structured into two main phases. The first phase involves the establishment of the evolutionary game and system dynamics models. This begins with the formulation of problem descriptions and assumptions, followed by the development of an evolutionary game model that includes a stable strategy analysis for each participant and equilibrium point analysis. The system dynamics model is then established to capture the dynamic interactions among stakeholders over time. In the second phase, numerical simulations are conducted to evaluate various policy scenarios. This includes sensitivity analysis to compare the effects of fixed taxes on developers and customers, as well as dynamic strategies such as green credits, dynamic public awareness campaigns, and dynamic customer green taxes. The results are then compared to assess the impact of these policies both individually and in combination. The subsequent sections of this paper discuss the findings of these simulations, their implications, and the broader theoretical, practical, and societal contributions of the research.

4.3.3 Tripartite evolutionary game model and system dynamics model

4.3.3.1 Problem descriptions and assumptions

The selection of government, developers, and customers as the primary stakeholders in this game-theoretic model is justified by their pivotal roles and interactions within the construction industry ecosystem. These three groups represent the key decision-makers who significantly influence the adoption of sustainable practices in construction. The government acts as the policy-maker, implementing regulations and incentives that shape the industry's direction. Developers, as the producers, make crucial decisions about adopting green technologies, practices, and the use of green material in their projects. Customers, through their purchasing power and preferences, drive market demand for sustainable construction. This tripartite model captures the essential dynamics of policy implementation, market forces, and consumer behavior, allowing for a comprehensive analysis of the factors influencing the transition to green construction practices. By focusing on these three stakeholders, the study can examine the complex interplay between regulatory pressures, economic considerations, and public awareness, providing insights into effective strategies for promoting sustainability in the construction industry.

Therefore, this study examines the interactions among key stakeholders in the construction industry—government, developers, and customers—and the role of banks in promoting green construction practices. We define the stakeholders and their interaction rules before constructing a tripartite evolutionary game model. In Fig. 4.2, directional arrows represent causality, indicating that one party's decisions influence another's. The government can choose to enforce green regulations through taxes or remain passive.

Developers decide between producing green products with environmentally friendly behavior or continuing traditional practices, while customers choose between purchasing green or conventional products. Banks play a significant role by offering reduced-interest loans to developers adopting green practices, encouraged by government incentives like green taxes.

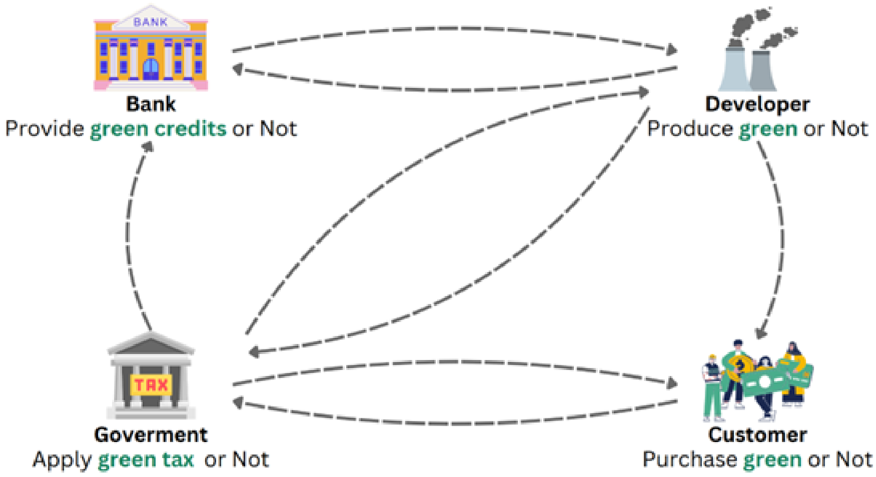


FIGURE 4.2. Relationship between stakeholders

Based on the above, we make the following assumptions:

Assumption 1: Game player. This study focuses on three primary stakeholders in the construction industry: the government, developers, and customers. For simplicity, we use "government" to denote policymakers with authority over tax policies. Banks, though influential by offering financial incentives based on government and developer actions, are not considered independent players, as their involvement is contingent on green tax application by the government and 'green' operations by developers. Additionally, we assume the availability of enough green products to meet construction demand.

Assumption 2: Action. The likelihood of customers opting for green products is a probability x, with the alternative choice of non-green products having probability $1-x$. Similarly, the probability of producers engaging in green production practices is y, while the probability of adhering to conventional production methods is $1 - y$. For the government's decision-making, z represents the probability of implementing a green tax policy, whereas $1 - z$ indicates the probability of opting out of regulatory supervision. These variables are all constrained within the range of 0 to 1.

Assumption 3: Payoff. In this model, customer utility from any purchase is denoted by U, representing the intrinsic value derived from acquiring a product [Franke and Schreier, 2008]. When customers opt for green products, they attain a utility R, which demonstrates the satisfaction utility gain from making environmentally friendly choices, influenced by the level of environmental public awareness [Li et al., 2021]. Higher public awareness typically enhances the utility gained from purchasing green products [Moser, 2015]. The variable β quantifies the greenness of a product, with higher values of β indicating greater environmental friendliness. However, customer satisfaction does not always directly correlate with the greenness of a product; for instance, customers may appreciate products labeled as green without a willingness to pay more for higher greenness levels [Royne et al., 2011]. To accommodate this, α is introduced to adjust β, reflecting the actual utility gain for customers from purchasing products of specific greenness.

On the other hand, when making a green purchase, customers incur an additional cost C_1, as it often costs more to buy a green product [Royne et al., 2011]. If the developers produce green products, customers gain an additional benefit D, representing the social and environmental benefits accrued [Manso et al., 2021]. Conversely, if the developers do not engage in green production, customers face an extra cost F, signifying the social and environmental losses incurred [Manso et al., 2021]. Should the government implement a green tax and customers choose non-green products, they must pay an additional green tax P_1. Furthermore, if developers also neglect green production, they often pass on a portion of their tax burden to customers later. This transfer is captured in our model as the developers' green tax P_2, with the transfer rate denoted by θ, indicating the extent to which customers bear the cost of non-green practices through increased prices.

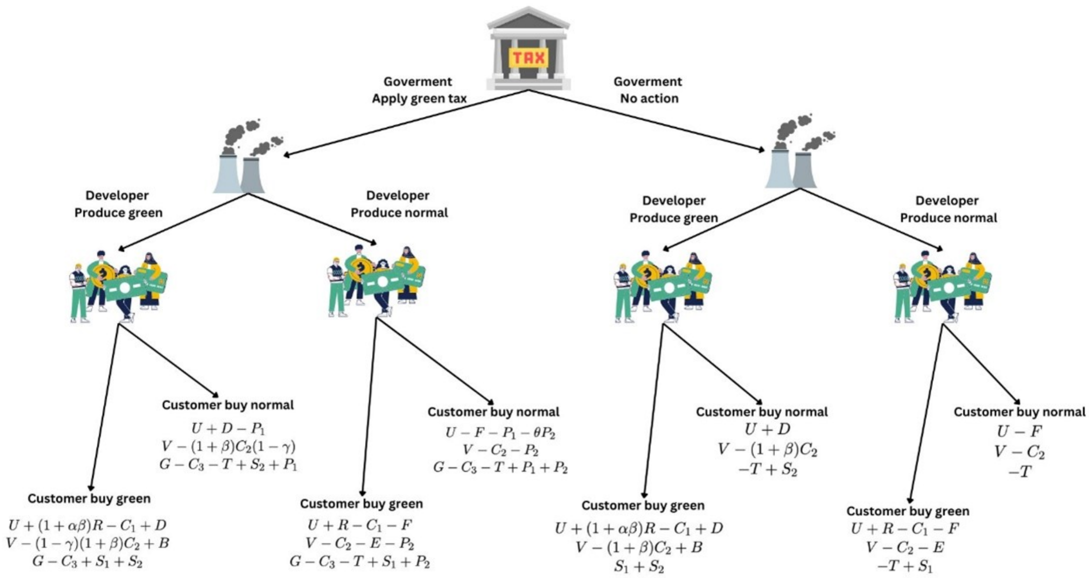


Figure 4.3. Evolutionary game tree

4.3.3.2 Evolutionary game model and equilibrium analysis

The payoff matrix of customers, developers, and governments was obtained in accordance with the model assumptions and parameter definitions, as shown in Fig. 4.3.

This study assumes that U_{ij} and U_i represent the expected return of the participants, where $i = 1, 2, 3$ represent customers (x), developers (y), and governments (z), respectively, and $j = 1, 2$ represent participants' two different decisions (i.e., green or not green). Per the choice matrix in Fig. 4.3, we can calculate the expected income of customers, developers, and governments. The specific procedures are as follows:

Customer's Expected Return U_1. The customer's payoff depends on the government's action z and the developer's action y. The expected return for customers can be calculated as:

$$U_1 = x \cdot U_{11} + (1 - x) \cdot U_{12} \tag{4.3}$$

Where U_{11} and U_{12} are the payoffs when customers choose green and not green purchase strategies, respectively. These payoffs are influenced by the developers' and government's decisions.

Developer's Expected Return U_2. The developer's payoff depends on the government's action z and the customer's action x. The expected return for developers can be calculated as:

$$U_2 = y \cdot U_{21} + (1 - y) \cdot U_{22} \tag{4.4}$$

Here, U_{21} and U_{22} are the payoffs when developers choose green and not green production strategies, respectively. These are calculated considering the costs, benefits, and the impact of government policies.

Government's Expected Return U_3. The government's payoff depends on the actions of both customers x and developers y. The expected return for governments can be calculated as:

$$U_3 = z \cdot U_{31} + (1 - z) \cdot U_{32} \tag{4.5}$$

Where U_{31} and U_{32} represent the payoffs when the government chooses to apply a green tax or not, respectively.

Detailed Payoff Calculations. Based on Eqs. 4.1 to 4.3, the U_{11}, U_{12}, U_{21}, U_{22}, U_{31}, and U_{32} are calculated as follows:

$$U_{11} = (1-z)y(U+(1+\alpha\beta)R-C_1+D)+zy(U+(1+\alpha\beta)R-C_1+D) \\ +z(1-y)(U+R-C_1-F)+(1-z)(1-y)(U+R-C_1-F) \quad (4.6)$$

Where U_{11} captures the scenario where customers choose to buy green buildings, developers produce green constructions, and the government applies green tax. Here, α represents the extra utility from the degree of greenness, β is the degree of greenness, R is the utility gain from buying green, C_1 is the additional cost of buying green, and D is the social and utility benefit when developers build green. F represents the social cost when developers do not build green.

For the scenario where customers do not buy green products, we have:

$$U_{12} = (U+D)(1-z)y+zy(U+D-P_1) \\ +z(1-y)(U-F-P_1-\theta P_2)+(1-z)(1-y)(U-F) \quad (4.7)$$

Here, P_1 and P_2 are taxes imposed on the customer and developer, respectively, for not choosing green. θ represents the cost transformation rate from the developer to the customer.

Developer's Payoff for Producing Green Buildings.

$$U_{21} = (1-z)x(V-(1+\beta)C_2+B)+zx(V-(1-\gamma)(1+\beta)C_2+B) \\ +z(1-x)(V-(1+\beta)C_2(1-\gamma))+(1-z)(1-x)(V-(1+\beta)C_2) \quad (4.8)$$

Here, V is the benefit for the developers when the product is sold, C_2 is the cost of a normal build, B represents the producer's extra benefit when producing green, and γ is the green credit from the bank that reduces operation costs when building green.

Developer's Payoff for Not Producing Green Buildings.

$$\begin{aligned} U_{22} = {} & (1 - z)x(V - C_2 - E) + zx(V - C_2 - E - P_2) \\ & + z(1 - x)(V - C_2 - P_2) + (1 - z)(1 - x)(V - C_2) \end{aligned} \tag{4.9}$$

E represents the producer's loss when they do not meet green demand, and P_2 is the tax imposed for not producing green.

Government's Payoff When Applying a Green Tax.

$$\begin{aligned} U_{31} = {} & (1 - x)y(G - C_3 - T + S_2 + P_1) + xy(G - C_3 + S_1 + S_2) \\ & + x(1 - y)(G - C_3 - T + S_1 + P_2) + (1 - x)(1 - y)(G - C_3 - T + P_1 + P_2) \end{aligned} \tag{4.10}$$

Here, G represents the social utility benefit from applying a green tax, C_3 is the management cost, T is the environmental cost when customers and developers do not cooperate greenly, and S_1 and S_2 represent environmental and utility benefits when customers and developers choose green, respectively. P_1 and P_2 are penalties for customers and developers not choosing green.

Government's Payoff When Not Applying a Green Tax.

$$\begin{aligned} U_{32} = {} & (1 - x)y(-T + S_2) + xy(S_1 + S_2) \\ & + x(1 - y)(-T + S_1) + (1 - x)(1 - y)(-T) \end{aligned} \tag{4.11}$$

This reflects the reduced benefits and increased environmental costs when the government refrains from imposing green taxes.

The replicator dynamic equations describe how the proportions of each strategy change over time among the population of customers, developers, and the government:

For Customers:

$$
\begin{aligned}
F(x) = \frac{dx}{dt} &= x(U_{11} - U_1) = x(1-x)(U_{11} - U_{12}) \\
&= x(1-x)(-C_1 + P_1 z - P_2 yz\theta + P_2 z\theta + Ry\alpha\beta + R)
\end{aligned} \tag{4.12}
$$

The proportion of customers choosing green products increases if the payoff U_{11} (buying green) is greater than U_{12} (not buying green). The factor $x(1-x)$ ensures the dynamics depend on both the payoff difference and the current proportion of customers choosing each strategy.

For Developers:

$$
\begin{aligned}
F(y) = \frac{dy}{dt} &= y(U_{21} - U_2) = y(1-y)(U_{21} - U_{22}) \\
&= y(1-y)(Bx + C_2\beta\gamma z - C_2\beta + C_2\gamma z + Ex + P_2 z)
\end{aligned} \tag{4.13}
$$

The proportion of developers opting to produce green buildings will increase if U_{21} (producing green) exceeds U_{22} (not producing green).

For Governments:

$$
\begin{aligned}
F(z) = \frac{dz}{dt} &= z(U_{31} - U_3) = z(1-z)(U_{31} - U_{32}) \\
&= z(1-z)(-C_3 + G - P_1 x + P_1 - P_2 y + P_2)
\end{aligned} \tag{4.14}
$$

The proportion of governments applying green taxes or incentives will increase if U_{31} (applying a green tax) results in a higher payoff than U_{32} (not applying a green tax).

The replicator dynamic equations, as shown in Eqs. 4.12 to 4.14, illustrate the temporal evolution of each stakeholder's likelihood of adopting a particular strategy. By setting the replicator dynamic equations for the three stakeholders to zero as $F(x) = \frac{dx}{dt} = 0$, $F(y) = \frac{dy}{dt} = 0$, and $F(z) = \frac{dz}{dt} = 0$, we can determine the equilibrium solutions of the evolutionary game. The analysis of the model reveals the existence of eight pure strategy

TABLE 4.3. Eigenvalues of Jacobin matrix

(x, y, z)	λ_1	λ_2	λ_3	Sign of λ_1	Sign of λ_2	Sign of λ_3	**Stability**	**Stability Condition**
(0, 0, 0)	$R - C_1$	$-\beta C_2$	$G - C_3 + P_1 + P_2$	-	-	+	No	No stability condition
(0, 0, 1)	$P_1 + \theta P_2 + R - C_1$	$-\beta C_2 + C_2\gamma$ $+C_2\gamma\beta + P_2$	$-(G - C_3 + P_1 + P_2)$	*	*	-	Yes	$P_1 < -\theta P_2 - R + C_1$ $P_2 < \beta C_2 - C_2\gamma - C_2\gamma\beta$
(0, 1, 0)	$\alpha\beta R + R - C_1$	$-\beta C_2$	$G - C_3 + P_1$	*	+	+	No	No stability condition
(0, 1, 1)	$\alpha\beta R + P_1 + R - C_1$	$-\beta C_2 + C_2\gamma$ $+C_2\gamma\beta + P_2$	$-(G - C_3 + P_1)$	*	*	-	Yes	$P_1 < -R + C_1 - \alpha\beta R$ $P_2 > \beta C_2 - C_2\gamma - C_2\gamma\beta$
(1, 0, 0)	$-(R - C_1)$	$-\beta C_2 + B + E$	$G - C_3 + P_2$	+	*	+	No	No stability condition
(1, 0, 1)	$-(P_1 + \theta P_2 + R - C_1)$	$-\beta C_2 + B + E+$ $C_2\gamma + C_2\gamma\beta + P_2$	$-(G - C_3 + P_2)$	*	*	-	Yes	$P_1 > -R + C_1 - \theta P_2$ $P_2 < \beta C_2 - B - E - C_2\gamma - C_2\gamma\beta$
(1, 1, 0)	$-(\alpha\beta R + R - C_1)$	$-\beta C_2 + B + E$	$G - C_3$	*	*	+	No	No stability condition
(1, 1, 1)	$-(\alpha\beta R + P_1 + R - C_1)$	$-\beta C_2 + B + E+$ $C_2\gamma + C_2\gamma\beta + P_2$	$-(G - C_3)$	*	*	-	Yes	$P_1 > -R + C_1 - \alpha\beta R$ $P_2 > \beta C_2 - B - E - C_2\gamma - C_2\gamma\beta$

equilibrium solutions. These are represented by the combinations $(0,0,0)$, $(0,1,0)$, $(0,0,1)$, $(0,1,1)$, $(1,0,0)$, $(1,1,0)$, $(1,0,1)$, and $(1,1,1)$, each indicating the strategic choices across the stakeholders—government, developers, and customers—where '1' denotes the adoption of a green strategy and '0' the opposite.

The Jacobin matrix for $F(x)$, $F(y)$, and $F(z)$ is shown as:

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{bmatrix} \tag{4.15}$$

The Jacobin matrix, as in Eq. 4.15, for the tripartite evolutionary game model facilitates the analysis of the system's stability and dynamics. According to [Lyapunov, 1992], only when the equilibrium point is a pure strategy Nash equilibrium can it become an asymptotically stable equilibrium point. So mixed strategy equilibrium solutions cannot become evolutionary stability strategies. The stability of the eight pure strategy equilibrium points is analyzed using this method by judging the sign properties of the eigenvalues of the Jacobin matrix. The necessary and sufficient condition for becoming the evolutionary stability strategy is that all the eigenvalues of the Jacobin matrix (4.15) have negative real parts [Friedman, 1991, Weibull, 1995].

We substitute eight pure strategy equilibrium points (x, y, z) with $x = \{0, 1\}$, $y = \{0, 1\}$, and $z = \{0, 1\}$ into diagonal of Jacobin matrix, and analyze the sign properties of eigenvalues λ_1, λ_2, and λ_3. Here, λ_1 represents the solution when for $(x, y, z), x = \{0, 1\}$, λ_2 corresponds to the case when $y = \{0, 1\}$, and λ_3 represents the solution for $z = \{0, 1\}$. This analysis aids in determining whether the strategies can become evolutionarily stable and explains the corresponding stability conditions. As listed in Table 4.3, the columns λ_1, λ_2, and λ_3 represent the solution of each element on $\mathrm{diag}(J)$ based on various (x, y, z), where J is the Jacobin matrix we calculated before. The sign of λ_1, λ_2, and λ_3 are based on the assumption $R - C_1 < 0$ and $G - C_3 > 0$. * represents the sign which can be "+" or "−" depending on conditions. There are potential stable conditions when the value is negative.

The analysis indicates that strategies $(0, 0, 0)$, $(0, 1, 0)$, $(1, 0, 0)$, and $(1, 1, 0)$ are not evolutionarily stable, pointing to system instability when the government doesn't implement a green tax. This is consistent with the real-world tendency for lower green practice adoption without government intervention. Conversely, strategies $(0, 0, 1)$, $(0, 1, 1)$, $(1, 0, 1)$, and $(1, 1, 1)$ could be stable, depending on the green tax's design on customers and developers. Nonetheless, failure to meet stability conditions through tax design could render these equilibria unachievable, highlighting the tax design's crucial impact on system stability and outcomes.

4.3.4 System Dynamics Model Establishment

Combining evolutionary game theory with system dynamics provides a comprehensive framework for analyzing complex stakeholder interactions and decision-making over time. Evolutionary game theory captures the adaptive strategies of stakeholders, while system dynamics models feedback loops, time delays, and system-wide effects. Together, they offer a deeper understanding of how policies and incentives shape long-term behaviors, leading to more effective strategies for promoting sustainable practices in

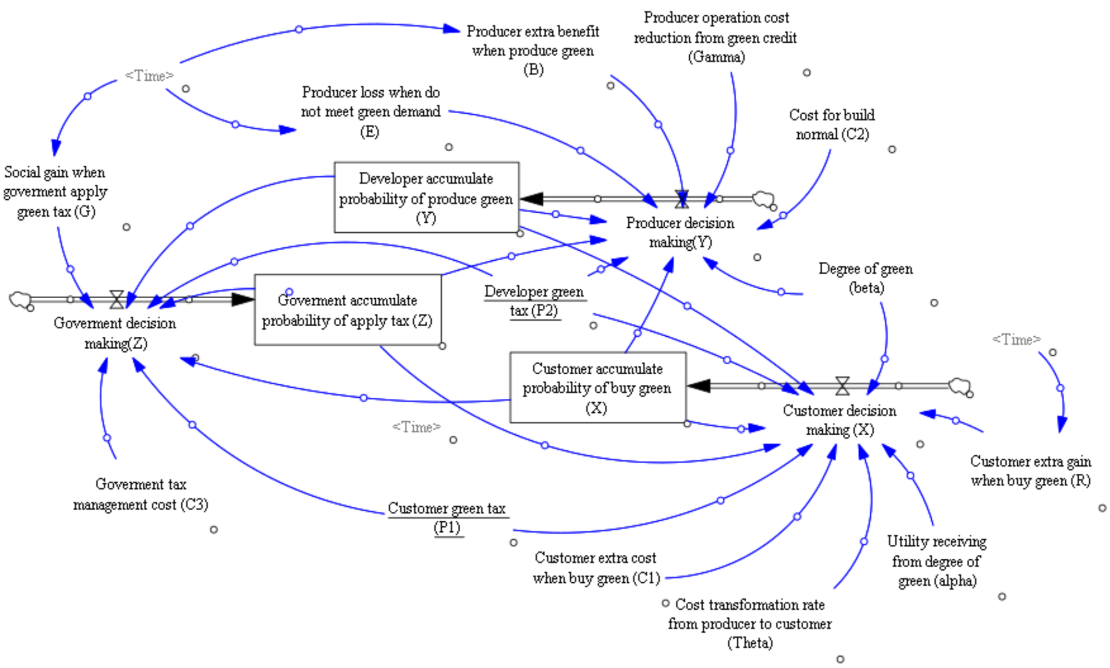


FIGURE 4.4. System dynamics model of evolutionary game in the construction industry

complex environments like green construction. This section builds upon the theoretical analysis of evolutionary game theory presented earlier and further conducts a numerical simulation analysis.

Given the large number of variables and parameters involved in this study, along with the complexity and challenges of measuring their relationships in real-world scenarios (e.g., utility gain when purchasing green products), the numerical simulation in this research does not rely on parameter settings from specific cases. However, to ensure the generalizability and robustness of the simulation results, this section adopts parameter settings from authoritative published studies for most variables and parameters. For parameters and variables lacking direct data sources, relevant information was obtained through interviews with experienced experts in the field, allowing for parameter calibration. Additionally, considering that the numerical differences among variables should reflect real-world conditions and that parameter calibration should satisfy the existence of the ESS presented in Table 4.3, adjustments and refinements were made to the parameter values accordingly. The initial parameter settings are detailed in Appendix Table 4.2. As shown in Figure 4.4, the system dynamics model used in this study is created with Vensim software. This model, specifically designed for the construction industry, is based on replicator dynamics equations (4.12) to (4.14), and comprises three subsystems: customers, developers, and government. Initially, the probability of green choices is set at 5%, reflecting low initial green behavior. The model prioritizes structural integrity over parameter precision and uses simulations to assess the impact of external variables on equilibrium stability. Parameters are sourced from online databases, empirical studies, or estimated for stability. The model's equations ensure consistent representation of system interactions. Validation tests, including model check, reality check, and unit check, were conducted to ensure accuracy. Additionally, the model's results were cross-verified with evolutionary game analysis for further validation.

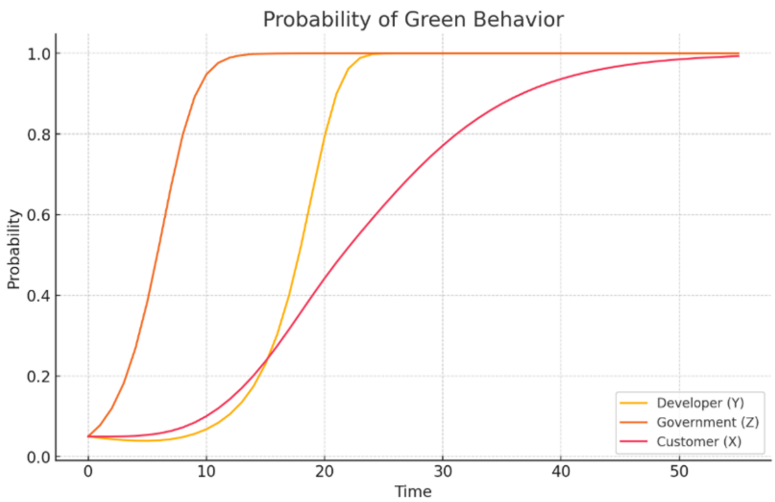


FIGURE 4.5. Evolution result from base model (1,1,1).

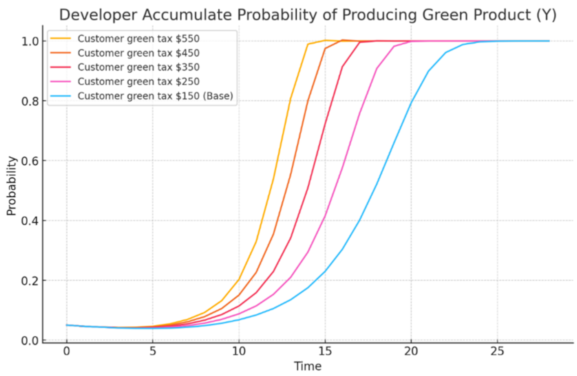
4.4 Numerical simulation

Based on the above analysis, four evolutionary stable strategies exist under certain conditions. However, our focus is on the strategy $(1, 1, 1)$, where all stakeholders act greenly. This section presents numerical simulations for the $(1, 1, 1)$ stability strategy, visually depicting the stakeholders' dynamic evolution. This allows for examining the impact of key parameters on the evolutionary trajectory and formulating policy recommendations.

The simulation results, shown in Fig. 4.5, demonstrate the evolution of the probabilities of government applying green tax, developers producing green products, and customers purchasing green products over time. Eventually, all three parties stabilize at the state $(1, 1, 1)$. The government acts first, followed by customers and then developers. Notably, customers are the second to increase their likelihood of choosing green products but the last to stabilize.

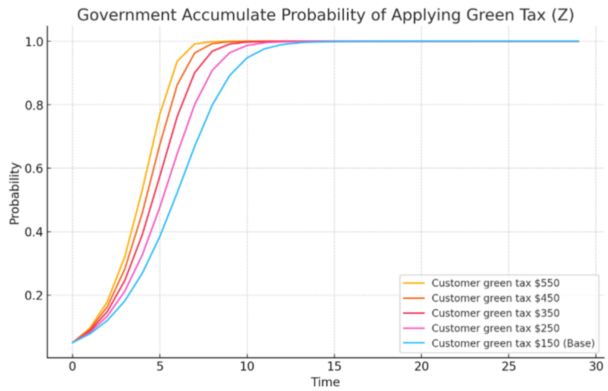
4.4.1 Sensitivity analysis of green tax, green public awareness, green credit, and strategy combination

Below sections analyzes the sensitivity of parameters related to government green taxes on customers and developers, public awareness of green practices, and green credits offered by banks (G, E, B, R, and γ) in the construction industry. The aim is to provide policy recommendations and insights for governmental bodies. Utilizing the specified parameter values, variations in one or more parameters are examined. In the resulting diagrams, we observed the impact on the probability of stakeholders adopting green behaviors over time. The diagrams visually demonstrate how policy changes can influence the industry's shift towards sustainability.



(A) Impact of customer green tax for customers.

(B) Impact of customer green tax for developers.



(C) Impact of customer green tax for government.

FIGURE 4.6. Impact of customer green tax.

4.4.1.1 Green Tax on Customer (P_1)

To assess the impact of customer green tax policy on stakeholders' evolutionary behavior, the study varies P_1 (\$150, \$250, \$350, \$450, \$550) while keeping other parameters constant. The results are shown in Figs. 4.6a, 4.6b, and 4.6c. The analysis indicates that higher green taxes accelerate the adoption of green behaviors among stakeholders. However, the rate of behavior change slows with each tax increase. For example, the time for customers to fully shift to green products decreases from over 100 to 69 decision rounds when the tax rises from \$150 to \$250, but only from 37 to 29 decision rounds when the tax increases from \$450 to \$550. This demonstrates diminishing returns at

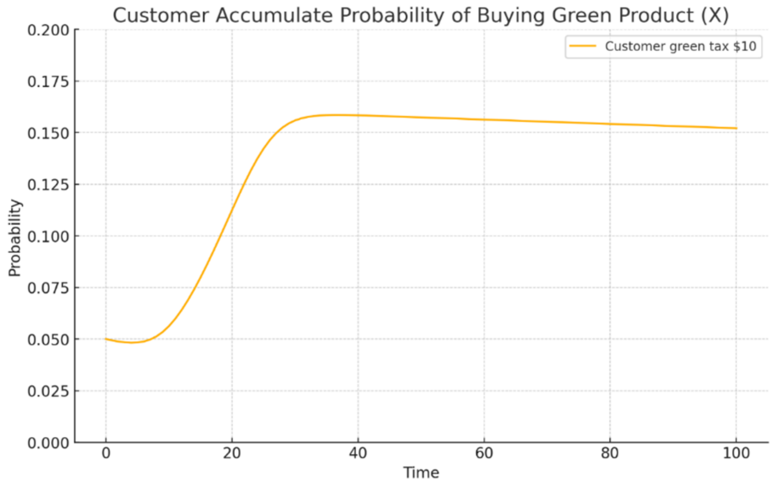


FIGURE 4.7. The probability of customer choosing green product when the customer green tax is \$10.

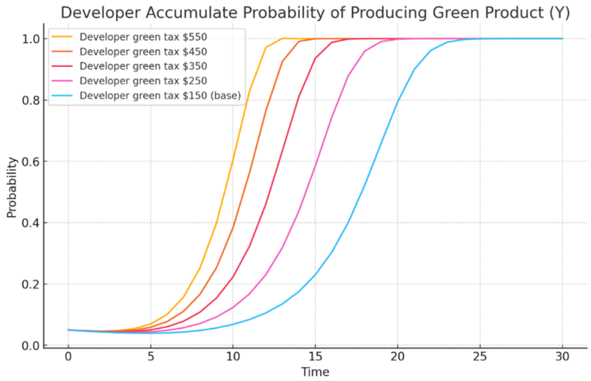
higher tax levels, suggesting a need for a balanced tax rate to effectively promote green practices. This trend also applies to developers and the government.

Additionally, the results are consistent with evolutionary game theory principles, where excessively high tax rates can destabilize the system by triggering resistance among stakeholders. The study also shows that for a stable $(1, 1, 1)$ state, the green tax on customers (P_1) must meet certain thresholds; if P_1 is too low, as in the case where it is set at \$10, the probability of customers choosing green products never reaches 1, instead fluctuating around 15%, as depicted in Fig. 4.7.

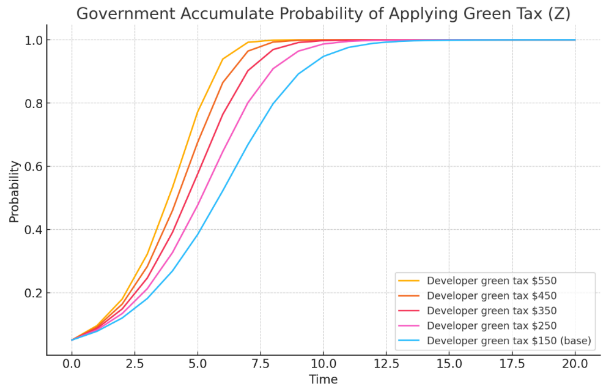
4.4.1.2 Green Tax on Developer (P_2)

To analyze the impact of developer green tax P_2 on stakeholders' evolutionary behavior, this study sets P_2 at \$150, \$250, \$350, \$450, and \$550, keeping other parameters constant. The results are shown in Figs. 4.8a, 4.8b, and 4.8c. Similar to P_1, increasing P_2 accelerates the adoption of green behaviors among the government and developers, but the rate of behavior change slows with each tax increase. However, P_2's impact on customer behavior is minor, with only slight differences in their shift towards green

(A) Impact of developer green tax for customers.



(B) Impact of developer green tax for developers.



(C) Impact of developer green tax for government.

FIGURE 4.8. Impact of developer green tax.

purchasing decisions. This suggests that while the developer green tax effectively influences government and developer behavior, its effect on customer behavior is less significant.

The differential impact of P_2 highlights the importance of designing policies that not only target the supply side but also consider the demand side. Although taxing developers drives green construction efforts, it may not fully address the issue of customer engagement, a key factor in market-driven sustainability transitions. Effective green construction strategies must account for both producers and consumers; otherwise, market saturation of green products can occur without corresponding consumer uptake.

This finding resonates with real-world cases where green construction projects faced difficulties due to low customer interest, even when developers adopted environmentally friendly practices.

4.4.1.3 Effect Comparison of Green Tax on Developer (P_2) and Green Tax on Customer (P_1)

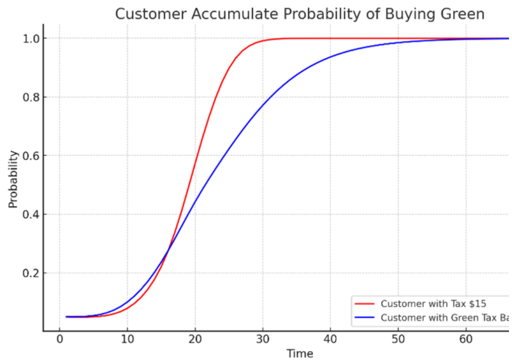
Both customer (P_1) and developer (P_2) taxes accelerate the adoption of green behaviors among stakeholders. However, P_1 tends to have a more immediate and pronounced effect, especially on customers. This difference arises because developers typically pass a portion of their green tax costs onto customers, indirectly influencing purchasing decisions. As a result, P_1 is a more direct and potentially effective tool for promoting customer green behavior.

Nonetheless, the diminishing returns observed with incremental tax increases for both P_1 and P_2 highlight the importance of setting balanced tax rates that promote sustainability without imposing excessive burdens.

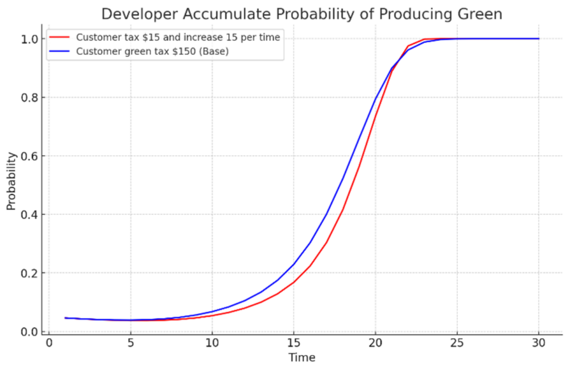
4.4.2 Dynamic Green Tax on Customer (P_1)

Research indicates that high taxes can discourage investment and limit market participation [Liu et al., 2023], with the construction industry often transferring additional costs to consumers, thereby impacting the cost of living. To promote behavioral changes, a dynamic green tax strategy is recommended, beginning at a low rate and incrementally increasing, allowing individuals time to adapt.

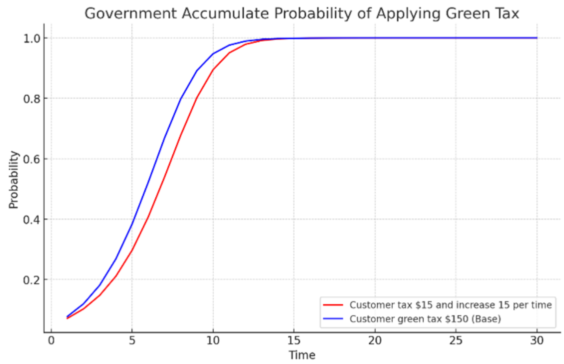
In this study, a dynamic tax strategy for customers starts at \$15 and increases by \$15 per decision round. Figures 4.9a, 4.9b, and 4.9c demonstrate that while this approach initially results in slower behavior change compared to a fixed tax of \$150, it ultimately leads to faster adoption of green practices. In the early stages, the fixed tax model is



(A) Impact of dynamic customer green tax for customers.



(B) Impact of dynamic customer green tax for developers.



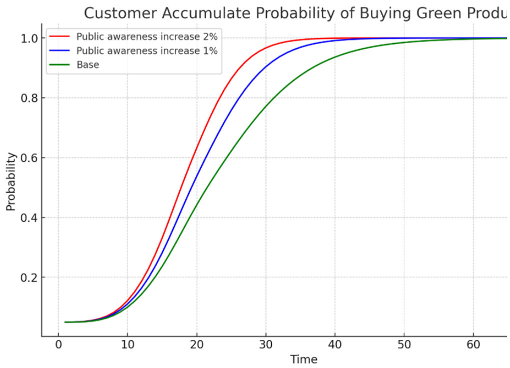
(C) Impact of dynamic customer green tax for government.

FIGURE 4.9. Impact of dynamic customer green tax.

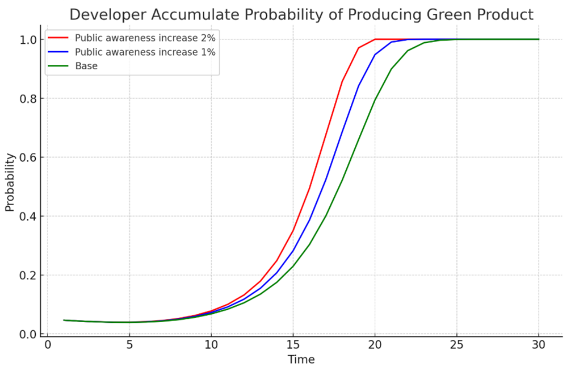
more effective at driving customer behavior changes, as it generates a quicker shift toward green products. However, as time progresses, the dynamic tax strategy overtakes the fixed tax model, significantly accelerating green adoption by reducing the time needed to reach behavioral stability by over 57% for customers.

Similarly, developers and the government also experience faster transitions under the dynamic model, as it allows for smoother adaptation to incremental cost increases. Although the government collects less tax revenue in the early phases, this reduction has a minimal effect on its behavior, with the long-term gains in green adoption outweighing the initial shortfall.

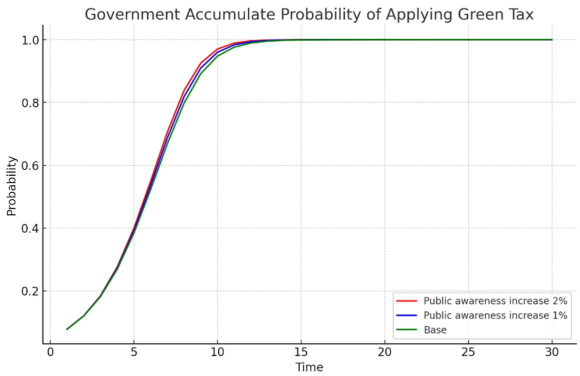
The results underscore that while a fixed tax may be advantageous initially, a dynamic tax strategy is more effective in promoting sustainable practices in the long run by balancing market stability with gradual adaptation.



(A) Impact of dynamic customer green tax for customers.



(B) Impact of dynamic customer green tax for developers.



(C) Impact of dynamic customer green tax for government.

Figure 4.10. Impact of dynamic customer green tax.

4.4.3 Dynamic Green Public Awareness

In our model, we consider parameters related to public awareness of green practices (G, E, B, and R from Table A.1), where an increase in these factors can significantly promote green practices. This study introduced a dynamic strategy to gradually increase public awareness, with these parameters rising by 1% and 2% per decision round while keeping other factors constant.

Figures 4.10a, 4.10b, and 4.10c show that heightened public awareness leads to faster adoption of green behaviors among all stakeholders. However, similar to the effects of dynamic taxation, the rate of behavior change diminishes with each incremental increase in public awareness. This strategy has the most substantial impact on customer behavior change, followed by developers, while having only a minor effect on government behavior.

These findings suggest that while dynamic public awareness campaigns are crucial for driving green practices, their influence may be most effective when combined with complementary strategies that can also target both developers and governmental actions.

4.4.4 Green Credit from Financial Institutions

Green credits from financial institutions, by providing financial incentives through reduced rates or favorable loan terms for sustainable projects, lower the costs of green construction, encouraging developers to adopt eco-friendly technologies and materials. In this study, green credit cost reduction rates for green practices were set at 5%, 10%, 15%, and 20%.

Figure 4.11 shows that the probability of developers adopting green practices increases with higher green credits, though at a diminishing rate. As expected, green credits have little to no impact on customers and the government. These findings suggest that while green credits are effective in motivating developers, they need to be integrated with other demand-side strategies to achieve broader sustainability goals.

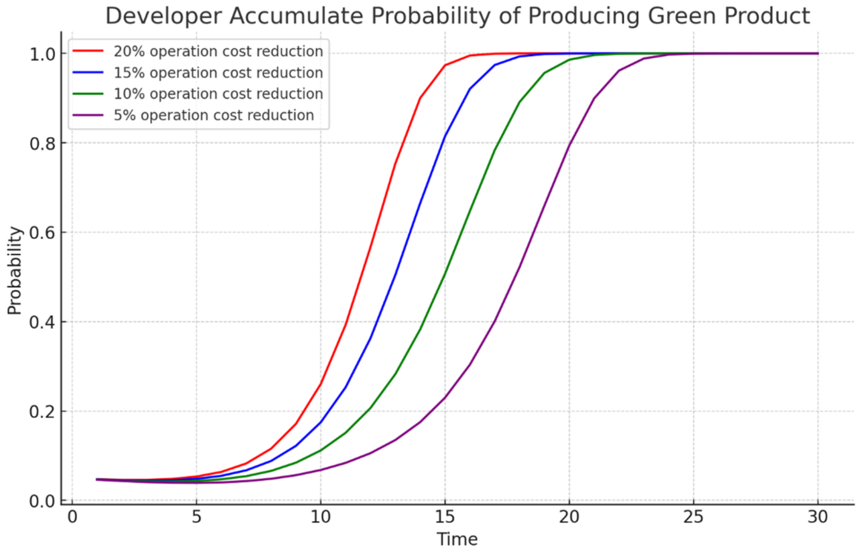


Figure 4.11. Impact of green credit operation cost reduction for developers.

4.4.5 Policy Combination

The analysis shows that various policies can impact the transition to green practices, with their effectiveness tending to diminish over time. A single policy approach may not be as effective as a comprehensive one, as overuse can lead to reduced effectiveness. For example, excessively high taxes may face market resistance, while too many public awareness campaigns may not proportionally boost engagement. Therefore, a balanced approach combining multiple policies, such as dynamic customer green taxes, public awareness campaigns, and green credits, can create a synergistic effect and promote sustainable practices more effectively in the construction industry.

In this section, we compare a combined policy approach to the base model, showing the benefits of a multifaceted strategy. By integrating policies such as a 10% green credit scheme for developers, a dynamic customer green tax starting at $15 and increasing by $15 per decision round, and a 1% increase in environmental utility gain to reflect growing public awareness, we avoid over-reliance on any single policy. This balanced approach mitigates potential resistance and fatigue from redundant or aggressive policies, increasing the viability of advancing sustainable practices.

As shown in Figs. 4.12a, 4.12b, 4.12c and Table 4.4, the policy combination outperforms every other pure policy, and any pure policy is better than the base policy in accelerating the transition to green behavior. Fig. 4.13 shows the dynamic evolution of stakeholder behaviors over time with a combined policy. The government was the first to adopt green practices, reaching a 99% probability of applying a green tax by the 13th decision round and full stability by the 25th decision round. Customers began shifting towards green purchases by the 5th decision round, achieving complete stability by the 40th decision round, motivated by government policies. Developers started adopting green practices from the 6th decision round, surpassing customer adoption by the 10th decision round and reaching full stability by the 20th decision round. This highlights developers' responsiveness to customer preferences and governmental policies in the green construction market, being the last to start but the first to fully embrace green practices. These findings highlight the importance of a strategic, phased approach that leverages the complementary strengths of various policy tools. While dynamic taxes and credits provide financial motivation, public awareness initiatives cultivate a cultural shift toward sustainability. The interaction of these elements creates a reinforcing cycle that drives long-term behavior change across all stakeholders, suggesting that a holistic approach is crucial for sustainable transitions in the construction industry.

4.5 Discussion

This study employed a novel combination of evolutionary game theory and system dynamics to analyze the adoption of green products in the construction industry, focusing on the interactions between government, developers, and customers. Our findings

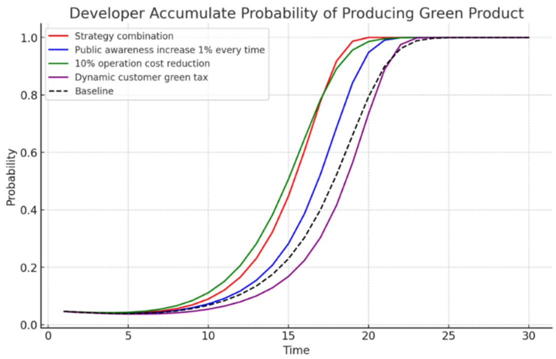
Table 4.4. Policy effectiveness comparison on time to reach stability

Stakeholder	**Policy**	**Number of Time Units to Reach Stability**
Customer	Dynamic customer green taxes	43
	Green credit	Over 100
	Public awareness campaigns	71
	Policy combination	40
	Base	Over 100
Developer	Dynamic customer green taxes	26
	Green credit	26
	Public awareness campaigns	23
	Policy combination	20
	Base	29
Government	Dynamic customer green taxes	28
	Green credit	31
	Public awareness campaigns	26
	Policy combination	25
	Base	30

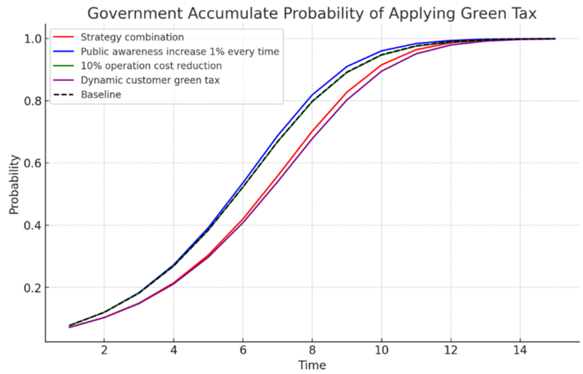
provide valuable insights into the complex dynamics of promoting sustainable practices in this sector and the effectiveness of various policy instruments.

Our simulation results demonstrate that all three parties - government, developers, and customers - eventually stabilize at the state $(1, 1, 1)$, representing full adoption of green practices. The sequential nature of this evolution, with government acting first, followed by customers and then developers, reflects the real-world dynamics of policy implementation and market response. This finding aligns with [Yuan et al., 2020], who found that while government initially leads industry in promoting sustainable practices, the need for intervention diminishes as the industry evolves. The study reveals that both customer (P_1) and developer (P_2) green taxes accelerate the adoption of green behaviors among stakeholders. However, we found that customer green taxes (P_1) tend to have a faster and more direct impact, especially on customer behavior. This finding builds upon the work of [Qiao et al., 2022] and [Liu et al., 2023], who confirmed the significant influence of green taxes on system evolution during green transition, by offering a more nuanced understanding of how taxes impact various stakeholders. Importantly, our results show

(A) Policy effectiveness comparison for customers.



(B) Policy effectiveness comparison for developers.



(C) Policy effectiveness comparison for government.

Figure 4.12. Policy effectiveness comparison.

diminishing returns with increasing tax rates, suggesting the need for a balanced approach. This addresses a gap identified in previous research, such as [Sun et al., 2023], which did not provide comprehensive solutions for balancing environmental goals with economic considerations.

The study highlights the significant impact of increasing public awareness on the adoption of green practices, particularly among customers and developers. This finding supports and extends previous research on the importance of public participation in promoting sustainable practices [Song et al., 2020]. Our dynamic modeling of public

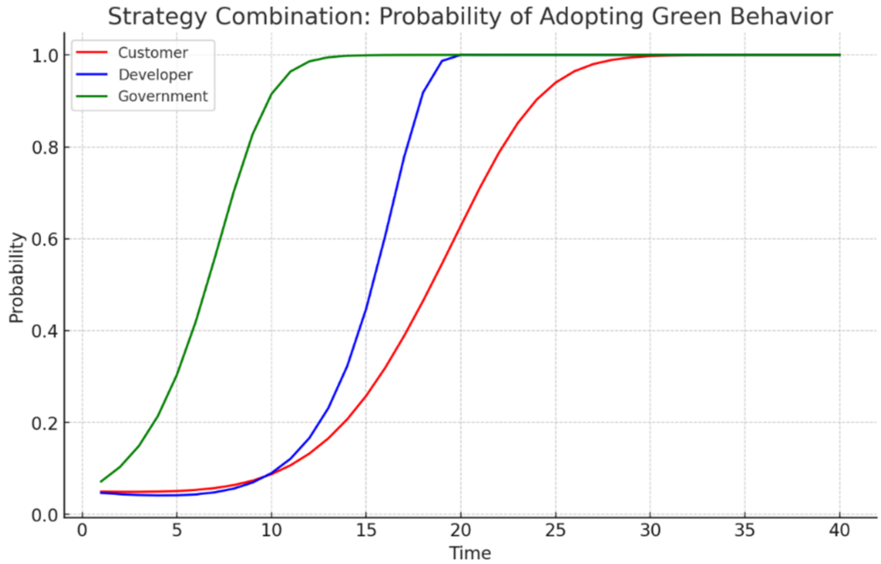


Figure 4.13. Policy combination impact comparison

awareness provides a more realistic representation of evolving social contexts, addressing a limitation in previous static models.

Our analysis of green credits from financial institutions shows a positive impact on developers' adoption of green practices, albeit with diminishing returns at higher credit levels. This finding adds to the work of [Deb et al., 2023] on green financing by providing a quantitative assessment of its effectiveness in the construction industry context.

A key finding of our study is the superior effectiveness of a combined policy approach over any single policy. By integrating dynamic customer green taxes, public awareness campaigns, and green credits, we demonstrate a synergistic effect in promoting sustainable practices. This comprehensive approach addresses the limitation noted by [Jiang et al., 2022] regarding the need for flexible and adaptive policy combinations.

4.5.1 Implications

The findings of this study have significant implications for theory and practice in promoting green products and sustainable practices in the construction industry. These implications are multifaceted and address various aspects of policy-making, stakeholder behavior, and industry practices.

4.5.1.1 Theoretical Implications

- **Dynamic Policy Modeling:** By incorporating dynamic variables such as incrementally increasing taxes and changing public awareness, our model provides a more realistic representation of policy implementation and its impacts over time. This approach allows for a nuanced understanding of how the effectiveness of policies may change as the market evolves, addressing a key gap in previous static models.
- **Multi-Policy Analysis:** Our research focuses on the combined effects of dynamic carbon tax incentives, public awareness campaigns, and green financing in promoting green construction. This comprehensive approach illuminates the complex interactions between different policy instruments and their collective impact on stakeholder behavior, extending beyond the single-policy focus of many previous studies.
- **Enhanced Decision-Making Insights:** The integration of environmental awareness and green finance considerations into our model provides deeper insights into stakeholder decision-making processes. This can help researchers and policymakers better understand the complex dynamics of sustainability transitions in the construction industry.
- **Methodological Innovation:** This study pioneers the combination of evolutionary game theory and system dynamics in analyzing green construction

practices among government, customers, and developers. This novel framework for dynamic policy analysis offers a more comprehensive examination of stakeholder interactions over time, providing unique insights into how various policies influence behavior.

4.5.1.2 Practical Implications

- **Policy Design:** Our findings suggest that policymakers should consider implementing dynamic green tax strategies rather than fixed high rates. Starting with lower taxes and gradually increasing them over time can lead to more effective and sustainable adoption of green practices.
- **Public Awareness Campaigns:** The significant impact of public awareness on green product adoption, especially among customers and developers, suggests that governments and industry associations should invest in sustained public education and awareness programs about the benefits of green construction.
- **Green Financing:** Financial institutions and policymakers should consider implementing green credit schemes to encourage developers to adopt sustainable practices. However, they should be aware of the diminishing returns at higher credit levels and design their programs accordingly.
- **Balanced Approach:** Our research demonstrates the superiority of a combined policy approach. Policymakers should aim to create a balanced mix of green taxes, public awareness campaigns, and financial incentives to promote sustainable practices most effectively.
- **Stakeholder-Specific Strategies:** Given the different response patterns of government, developers, and customers, policies and initiatives should be tailored to each stakeholder group for maximum effectiveness.
- **Long-term Planning:** The evolutionary nature of green practice adoption highlighted in our study suggests that policymakers and industry leaders should

adopt a long-term perspective in their sustainability strategies, allowing time for market adaptation and behavior change.

4.5.1.3 Societal Implications

- **Environmental Impact:** By providing insights into effective strategies for promoting green construction practices, this research contributes to broader efforts to reduce the construction industry's carbon footprint and overall environmental impact.
- **Economic Considerations:** The study's findings on the balance between environmental regulations and market participation can help in designing policies that promote sustainability without unduly burdening economic growth.
- **Consumer Behavior:** Our research sheds light on factors influencing consumer choices in green products, which can have broader implications for understanding and shaping sustainable consumer behavior beyond the construction industry.

4.6 Conclusions

Our research breaks new ground in understanding the complex dynamics of green product adoption in the construction industry. By merging evolutionary game theory with system dynamics, we have shed light on the intricate interplay between government policies, market forces, and stakeholder behaviors. This innovative approach has yielded valuable insights into the effectiveness of various strategies for promoting sustainable practices in one of the world's most resource-intensive sectors.

The results paint a compelling picture of the transition towards sustainability in construction. We observed a cascading effect in the adoption of green practices, initiated by government action, followed by customer shifts, and ultimately developer adaptations.

This sequence underscores the critical role of policy in catalyzing market-wide changes. Our analysis reveals that while both customer and developer-focused green taxes drive positive change, customer-oriented taxes demonstrate a more immediate and pronounced impact on behavior.

A key insight from our study is the effectiveness of dynamic policy approaches. We found that gradually increasing green tax strategies are more effective than static high-rate taxes in promoting sustainable practices. This finding challenges conventional wisdom and offers a more nuanced pathway for policy implementation. Additionally, our research highlights the substantial influence of public awareness campaigns and the positive, albeit diminishing, returns of green credit schemes for developers.

Perhaps the most significant outcome of our investigation is the clear superiority of a multifaceted policy approach. The synergistic effects observed when combining dynamic taxation, awareness campaigns, and financial incentives surpass the outcomes of any isolated strategy. This discovery provides a robust foundation for crafting comprehensive and effective sustainability policies in the construction sector.

These findings carry profound implications for policymakers and industry leaders. They call for a reimagining of how we approach sustainability in construction—advocating for flexible, stakeholder-specific strategies and long-term planning horizons. Our research suggests that success lies in balancing economic incentives with educational initiatives and financial support mechanisms, all calibrated to the unique dynamics of the construction industry.

However, we acknowledge the limitations of our study. The model we have developed, while innovative, is a simplified representation of an incredibly complex industry. The variability of construction markets across different countries and regions may limit the universal applicability of our findings. Furthermore, accurately quantifying certain variables, such as the costs of government oversight or the benefits of enhanced social reputation, remains a challenge.

Looking ahead, there are rich opportunities for future research to build upon this foundation. Applying our model to specific real-world scenarios could yield valuable insights and help refine its predictive capabilities. Expanding the scope to include a broader range of stakeholders—from contractors to suppliers and research institutions—would provide a more comprehensive picture of the industry ecosystem. Cross-country comparative studies could illuminate how varying regulatory environments and market structures influence the adoption of green practices. Additionally, incorporating more sophisticated metrics for environmental impact and social benefits would enhance the model's depth and applicability.

CHAPTER 5

A distributionally robust chance constraint model to demand-responsive skip planning problem: A Case Study in Sydney

5.1 Introduction

Effective waste management is crucial for minimizing environmental impacts, especially in the construction and demolition (C&D) sector. Urbanization has significantly increased the production of C&D waste [Zhou et al., 2022], which now constitutes a substantial share of global waste. For instance, it accounts for approximately 44% of Australia's total waste output [Park and Tucker, 2017]. Such large quantities of C&D waste can lead to land degradation, resource depletion, and elevated greenhouse gas emissions [Li et al., 2022a]. Unlike many other type of waste, which is typically generated at predictable locations and intervals, C&D waste arises from project-specific activities that are sporadic and often lack a fixed location. As a result, traditional route-based collection methods—which depend on regular schedules and predefined pickup points—prove inadequate for managing irregular, spatially dispersed waste streams. To improve waste management efficiency, a demand-responsive approach has been adopted in some cities. For example, Sydney has implemented floating skip services, where rental and delivery activities are meticulously planned to balance truck drivers' workloads and ensure timely pickup of skips at the conclusion of their rental periods.

The demand-responsive skip service for waste management improves resource utilization by providing skips only when needed. However, the connections between the delivery and pickup activities of skips require decisions to be made over a multi-period planning horizon, which adds complexity to the decision-making process. Specifically, in demand-responsive skip services management, the operator is responsible for managing a fleet of trucks to rent and deliver empty skips to areas based on received demands within the required timeframe, and to pick up and return them to recycling facility once the rental period ends. When making current skip rental and delivery decisions, the decision-maker must consider the future pickup of these skips. Current rental and delivery activities must be meticulously planned to both ensure that truck drivers' workloads remain within operational limits and enable the timely pickup of rented skips at the conclusion of their rental periods. In general, the links between delivery and pickup activities require decisions to be made over a multi-period planning horizon. To the best of our knowledge, previous studies on waste skip management typically formulate the problem as a roll-on/roll-off vehicle problem with fixed locations for skip demand areas [Archetti and Speranza, 2005, Li et al., 2018, Rabbani et al., 2016, Aringhieri et al., 2018, Wøhlk and Laporte, 2022, Belenguer et al., 2024], which do not account for multi-period planning. In contrast, our study addresses a demand-responsive waste skip management problem that requires multi-period planning.

In addition to the multi-period planning requirement, uncertainty in travel times caused by factors such as congestion, roadworks, and weather—further complicates the planning process. These uncertainties can lead to task delays and may result in truck drivers being overworked. Typically, to address the travel-time uncertainty, one may adopt an empirical optimization method such as stochastic programming (SP), where a set of scenarios with probabilities based on historical travel-time data are considered in the model. At the same time, a chance-constraint is employed under these scenarios to ensure that the violation probability of the workload of the truck drivers does not exceed a predetermined threshold. However, one short fall of the empirical optimization is: the distributions composed by scenarios may not be well approximate the true distribution, especially when the distribution is non-stationary or historical data samples are limited

[Bertsimas et al., 2019, Wang et al., 2023]. Besides, the stochastic programming method may require a large number of samples to approximate the true distribution, which is computational expensive under a multi-period planning optimization problem as we considered. Unlike empirical optimization methods, the distributionally robust optimization (DRO) approach does not depend on a single empirical distribution. Instead, it leverages a set of distributions, known as the ambiguity set, to better represent the true distribution.

This approach has been successfully applied in areas such as vehicle repositioning [Chen et al., 2024], facility location [Meng et al., 2024], and surgery scheduling [Wang et al., 2023], demonstrating its effectiveness in addressing distributional ambiguity.

In this work, we consider an optimization problem arising from demand-responsive waste recycling manner (such as the C&D waste skip management in Sydney). We formulate this problem over a multi-period planning horizon, aiming to optimize the assignment and scheduling of a fleet of trucks for renting and delivering empty skips to demand areas within the required timeframe, as well as picking up and returning them to recycling facilities once the rental period ends. Decisions related to vehicle assignment, scheduling, and the pickup and delivery of skips are optimized under travel-time uncertainties. The problem is formulated within a distributionally robust optimization framework, utilizing a series of chance constraints to ensure the workload limitations of truck drivers are respected under travel-time uncertainties.

To the best of our knowledge, this is the first attempt to model the demand-responsive skips management using distributionally robust chance constraints. Rather than relying on a single probability distribution, our ambiguity sets incorporate a family of distributions using essential statistical information (such as means, deviations, and support bounds), ensuring solutions that remain feasible and cost-effective across a wide range of out-of-sample scenarios. This ensures that operational plans are not only adaptable to fluctuating traffic conditions, but also resilient against extreme delays. Additionally, we enhance operational realism by exploring the way of pickup and delivery of the skips and conclude them into three fundamental types, improving overall efficiency of the model.

We evaluate the model's performance using real-world data from the Sydney metropolitan area. Extensive computational experiments examine the impact of varying travel-time uncertainty distributions, operational constraints (including driver working hours and truck fixed costs), and network configurations (such as the number of recycling facilities). We also quantify the Price of Robustness, providing insights into the trade-offs between cost efficiency and risk mitigation. These analyses shed light on how operational levers can be adjusted to find an optimal balance between system resilience, economic viability, and sustainability goals.

This study makes three main contributions to the literature on C&D waste management and related routing problems:

(1) **Novel Multi-Period Skips Management Optimization Model:** We propose a new optimization framework tailored to the demand-responsive skips management problem. Unlike traditional roll-on/roll-off vehicle problems for skips management, which optimize pickup and delivery of skips within a single period, our model accommodates multiple consecutive delivery and pickup tasks over a multi-period planning horizon. This approach enables a more precise representation of demand-responsive skip rental patterns, effectively capturing the dynamic and practical requirements of real-world applications.

(2) **Incorporation of Travel Time Uncertainty via Distributionally Robust Optimization:** We integrate a distributionally robust chance-constrained approach to explicitly handle travel time variability. By not committing to a single assumed probability distribution, our model ensures that solutions remain feasible and cost-effective across a family of distributions. This robust handling of uncertainty provides practitioners with reliable operational plans that mitigate risks associated with traffic congestion and other unpredictable factors.

(3) **Comprehensive Empirical Evaluation and Managerial Insights:** Drawing on real-world data from the Sydney area, we rigorously evaluate our model under various network configurations, operating conditions, and robustness levels. The results highlight clear trade-offs between operational efficiency and reliability, offering insights into the strategic deployment of recycling facilities, vehicle assignment, and robust planning parameters. These findings are directly applicable to management practice, supporting more informed decision-making and contributing to the development of more sustainable, adaptive, and resilient C&D waste management operations.

The remainder of this paper is organized as follows. Section 5.2 reviews the existing literature on C&D waste management and related optimization problems. Section 5.4 formally states the problem and presents the proposed mathematical model, detailing the unique operational features and constraints of skip services, as well as the travel time uncertainty handling. Section 5.5 introduces the case study context, including data sources, demand characterization, and implementation details. Section 5.5 discusses the performance of the proposed model under various uncertainty scenarios, highlighting its robustness and scalability. Finally, Section 5.6 concludes the paper by summarizing the main contributions, discussing managerial insights, and suggesting future research directions.

5.2 Literature review

This section explores the existing literature relevant to C&D waste logistics. The review includes studies on the roll-on/roll-off vehicle task assignment and various optimization techniques designed to address uncertainty in logistical operations. These works provide the foundation for understanding the complexities of skip-based C&D waste management, which will be discussed in the subsections below.

5.2.1 Skips waste management

Previous research has predominantly explored skip logistics in C&D waste management through the framework of roll-on/roll-off vehicle task assignment researches [Archetti and Speranza, 2005, De Meulemeester et al., 1997, Belenguer et al., 2024, Wøhlk and Laporte, 2022, Li et al., 2018, Wy et al., 2013]. While these studies have laid a solid groundwork for optimizing container-based waste collection and transportation, they do not fully capture the distinctive operational requirements of C&D skip services.

A fundamental mismatch lies in how vehicles are modeled. Most roll-on/roll-off vehicle studies assume that trucks carry multiple containers simultaneously [Li et al., 2018, Wøhlk and Laporte, 2022, Belenguer et al., 2024], a premise incompatible with C&D skip services, where the large size and weight of each skip restrict trucks to transporting a single unit per trip. This constraint not only demands more nuanced routing and scheduling strategies but also intensifies the complexity of task assignments. Equally important is the oversimplification of operational tasks, as existing research largely concentrates on basic round-trip operations—either delivering an empty container and returning to the depot or moving waste directly to a disposal site [Rabbani et al., 2016, Yazdani et al., 2021, Wy et al., 2013]. Such models often fail to incorporate the intricate, multi-task nature of skip services, wherein a single outing may involve delivering an empty skip, retrieving one that is due for collection, and transporting it to a treatment facility. These multi-task trips are crucial for minimizing empty travel, improving resource utilization, and enhancing overall efficiency. Additionally, the commonly studied bin swap method [Archetti and Speranza, 2005, Rabbani et al., 2016, Aringhieri et al., 2018], which assumes instant exchanges of bin that is due for collection for empty ones, fails to accommodate the time-dependent, rental-based nature of skip services. Fixed rental durations introduce a temporal dimension that allows for more precise and forward-looking scheduling decisions, a complexity that current models do not fully address. Finally, current research often neglects essential operational details, including the procurement of empty skips and the strategic coordination with waste treatment facilities [Raucq et al., 2019]. These considerations significantly influence task assignments and must be integrated into models to reflect real-world constraints, such as driver working hours, environmental regulations, and evolving waste treatment capacities. Without these elements, solutions risk being overly simplistic and less effective when translated into practice.

Skip management problems share similarities with drone assignment and one-commodity delivery problems, as both involve a single-unit capacity constraint—drones typically carry a single item per trip, similar to skip trucks transporting one skip at a time. However, our study extends this paradigm by introducing additional operational complexities such as spatial delivery radii, driver working time constraints, and a distributionally robust chance-constrained framework to handle travel-time uncertainty, while concluding the pickup and delivery of skips into three fundamental types of operations: delivering an empty skip to a location and returning to the depot, collecting a rented skip and returning it to a recycling facility, and combining delivery and pickup tasks of two locations within a single trip. Also, unlike roll-on/roll-off studies for skips management, which primarily address single-period operations, our demand-responsive skip management problem integrates links between delivery and pickup activities over a multi-period planning horizon, requiring decision-makers to optimize current skip rental and delivery tasks while planning for future pickups at the end of rental periods. By ensuring all resource usage remain within operational limits and effectively balancing current and future demands, our approach tackles a fundamentally different optimization problem, integrating demand responsiveness, multi-period planning, and distributionally robust uncertainty handling to better reflect the practical challenges of skip logistics in C&D waste management.

5.2.2 Optimization under uncertainty

Optimization under uncertainty has been a cornerstone of decision-making in complex systems, evolving significantly over the decades. The foundational approaches—stochastic programming (SP) and robust optimization (RO)—have been extensively studied and applied. SP assumes precise knowledge of the probability distribution of uncertain parameters, optimizing the expected objective function [Shapiro et al., 2021, Birge and Louveaux, 2011]. However, this reliance on precise distributions makes SP vulnerable to estimation errors, particularly in high-dimensional settings, leading to the so-called "optimizer's curse" [Smith and Winkler, 2006].

Conversely, RO circumvents the need for probability distributions by assuming uncertain parameters belong to deterministic sets (e.g., ellipsoids or polyhedra) and optimizing for the worst-case outcomes [Ben-Tal and Nemirovski, 2000, Bertsimas and Sim, 2004]. While computationally appealing, RO is often criticized for its excessive conservatism, particularly in settings requiring operational flexibility. DRO provides a middle ground between SP and RO, optimizing the worst-case expectation over a family of distributions known as the ambiguity set. This concept was first introduced by [Scarf, 1957] for inventory management under moment constraints and has since been generalized to diverse applications [Rahimian and Mehrotra, 2022]. DRO balances robustness and flexibility, allowing partial probabilistic information to guide decision-making.

The choice of ambiguity sets is pivotal in DRO, as it effectively defines the breadth and nature of the uncertainty under consideration. Moment-based ambiguity sets, which constrain the distribution using known statistical properties such as means and variances, are often favored for their computational tractability [Scarf, 1957, Delage and Ye, 2010]. However, relying solely on lower-order moments can sometimes produce overly conservative solutions, since multiple, fundamentally different distributions may share identical moment values [Wiesemann et al., 2014]. This challenge underscores the need for more nuanced constructs that balance robustness, accuracy, and tractability in the face of uncertainty. Distance-based ambiguity sets, such as those defined using Wasserstein metrics, have emerged as a robust alternative. These sets leverage geometric measures to quantify the closeness of distributions, offering advantages in high-dimensional and data-driven contexts [Mohajerin Esfahani and Kuhn, 2018, Blanchet et al., 2022]. Wasserstein-based sets are particularly effective in balancing empirical adaptability and computational efficiency, making them suitable for large-scale applications. Recent advances in DRO include the development of decision-dependent ambiguity sets that account for evolving distributions influenced by decisions [Basciftci et al., 2021] and scalable algorithms for solving DRO problems in high-dimensional spaces [Mehta et al., 2024]. Additionally, DRO has been integrated into machine learning frameworks, enhancing robustness against distributional shifts [Shafieezadeh-Abadeh et al., 2019].

This study breaks new ground by DRO to the domain of skip task assignments within the C&D waste management sector. By incorporating travel-time uncertainties—arising from factors like traffic congestion and roadworks—into a scenario-based DRO framework, our approach delivers solutions that are simultaneously practical, cost-effective, and resilient under a broad range of real-world conditions. To the best of our knowledge, this is the first work to leverage DRO methodologies in skip logistics.

Moreover, our framework offers significant performance advantages, yielding robust yet economically viable solutions that adapt effectively to uncertainty, reduce operational costs, and improve scheduling efficiency.

5.3 Theoretical Foundation of Distributionally Robust Optimization

This section provides the theoretical foundation for distributionally robust optimization (DRO) and explains why it was selected for addressing travel time uncertainty in skip logistics problems.

Robust optimization addresses decision-making under uncertainty by considering worst-case scenarios within predefined uncertainty sets. Classical robust optimization (RO) considers uncertain parameters $\tilde{\boldsymbol{\xi}}$ belonging to a deterministic uncertainty set $\mathcal{U}$ and solves $\min_{\boldsymbol{x}} \max_{\tilde{\boldsymbol{\xi}} \in \mathcal{U}} f(\boldsymbol{x}, \tilde{\boldsymbol{\xi}})$. While computationally tractable, RO often produces overly conservative solutions by optimizing for absolute worst-case scenarios that may be extremely unlikely in practice.

Stochastic programming (SP) assumes complete knowledge of the probability distribution $\mathbb{P}$ governing uncertain parameters and solves $\min_{\boldsymbol{x}} \mathbb{E}_{\mathbb{P}}[f(\boldsymbol{x}, \tilde{\boldsymbol{\xi}})]$. However, SP suffers from the "optimizer's curse" when the assumed distribution differs from reality, potentially leading to poor out-of-sample performance. This is particularly problematic in urban logistics where travel time distributions are non-stationary and historical data may be limited.

Distributionally robust optimization bridges this gap by considering the worst-case expectation over a family of probability distributions, known as an ambiguity set $\mathcal{F}$: $\min_{\boldsymbol{x}} \sup_{\mathbb{P} \in \mathcal{F}} \mathbb{E}_{\mathbb{P}}[f(\boldsymbol{x}, \tilde{\boldsymbol{\xi}})]$. The ambiguity set captures distributional uncertainty by including all distributions consistent with available information such as moments, support bounds, or distance from empirical distributions. This provides balanced conservatism, avoiding RO's excessive pessimism while offering robustness against SP's distributional misspecification.

The construction of ambiguity sets is crucial for DRO performance. Moment-based ambiguity sets constrain distributions using statistical moments: $\mathcal{F}_{\text{moment}} = \{\mathbb{P} : \mathbb{E}_{\mathbb{P}}[\tilde{\boldsymbol{\xi}}] = \boldsymbol{\mu}, \text{Var}_{\mathbb{P}}(\tilde{\boldsymbol{\xi}}) \preceq \boldsymbol{\Sigma}, \text{supp}(\mathbb{P}) \subseteq \mathcal{D}\}$. Distance-based sets include distributions within specified distance from reference distributions: $\mathcal{F}_{\text{distance}} = \{\mathbb{P} : d(\mathbb{P}, \hat{\mathbb{P}}) \leq \rho\}$ where $d(\cdot, \cdot)$ represents statistical distance and $\hat{\mathbb{P}}$ is the empirical distribution.

For chance constraints limiting driver working hours, the standard formulation $\mathbb{P}(g(\boldsymbol{x}, \tilde{\boldsymbol{\xi}}) \leq 0) \geq 1 - \epsilon$ becomes distributionally robust: $\inf_{\mathbb{P} \in \mathcal{F}} \mathbb{P}(g(\boldsymbol{x}, \tilde{\boldsymbol{\xi}}) \leq 0) \geq 1 - \epsilon$. This ensures constraint satisfaction across all distributions in the ambiguity set, providing robustness against distributional uncertainty while maintaining computational tractability through reformulations.

We selected DRO for skip logistics based on several compelling factors. Travel times in urban environments exhibit non-stationary patterns varying by time, weather, and construction activities, while comprehensive historical data may be sparse for specific routes. The tail risk of extreme delays can severely impact operations, making robustness crucial for maintaining service quality and regulatory compliance. Skip logistics operations demand high reliability since violations of driver working hour limits have legal and safety implications, while consistent performance across varying conditions maintains customer satisfaction.

From a computational perspective, DRO offers practical advantages including tractable reformulations through our moment-based ambiguity sets, scalability by avoiding large scenario sets required by SP, and implementation ease using standard optimization solvers. Our DRO formulation provides finite-sample performance guarantees unlike SP's asymptotic properties, explicit control over robustness-performance trade-offs through ambiguity set parameters, and asymptotic consistency ensuring convergence to optimal solutions as data increases. This combination of theoretical rigor and practical applicability makes DRO particularly well-suited for urban waste management operations requiring reliable performance under uncertain conditions.

5.4 Problem statement and model formulation

In this section, we outline the problem of skip logistics for C&D waste management and establish a clear understanding of the notation used throughout the paper. The focus is on addressing operational challenges, including travel time uncertainties, single-container skip truck constraints, and multi-period scheduling. In Section 5.4.1, we present the formulation of the model, and in Section 5.4.2, we extend it to a distributionally robust model that incorporates travel-time uncertainty. The mathematical notations used in the paragraph are summarized in Table 5.1.

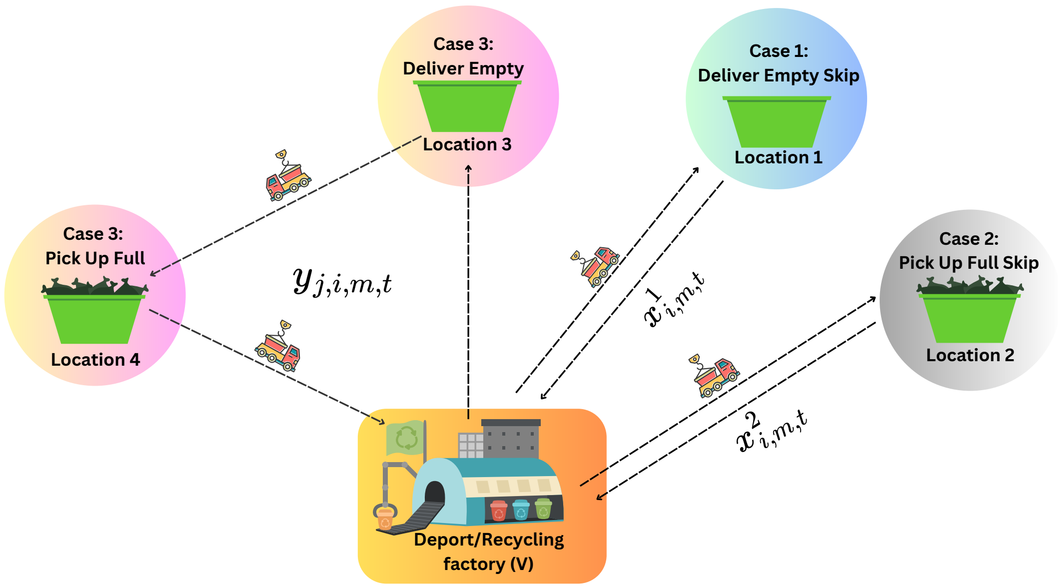


Figure 5.1. Skip delivery and collection operation cases

5.4.1 Problem description and model formulation

We consider a practical setting in which operators are tasked with assigning a fleet of vehicles to provide demand-responsive skip services. Specifically, customers—such as C&D waste generators, construction developers—submit requests for empty skips to the operators. In response, the operators allocate a fleet of vehicles to deliver the requested empty skips and collect rented skips at the end of their rental periods, transporting them between demand locations and recycling facilities within a defined planning horizon. In this context, we define four essential sets to model the problem. First, $\mathcal{I}$ represents the set of potential demand locations for skip rental services. Each node in this set corresponds to a potential skip location, and in each day in the planning horizon, it may have the status in such cases: 1. requiring an empty skip; 2. skip end of rental period; 3. has a skip in rental; 4. with no demand for skip services in current. The operators are required to response to the requirement of locations in status 1 and 2. Second, $\mathcal{M}$ represents the set of vehicles available for skip pick up and delivery, with the assumption that each vehicle can carry one skip per trip. This limitation arises because in many cases, such as the C&D waste management in Sydney, the C&D waste is very heavy, and carrying more than one skip could exceed the vehicle's capacity, compromising safety and efficiency while ensuring compliance with regulations. Next, $\mathcal{T}$ denotes the set of days within the planning horizon, allowing the operator to optimize vehicle assignments across different days to account for fluctuations in received demands for empty skips and the need to pick up rented skips at the end of their rental periods. Finally, $\mathcal{V}$ represents the recycling facilities where skips are delivered after being collected from C&D waste generation locations. These facilities process the contents of the skips, whether designated for recycling or general waste, and are assumed to maintain a sufficient inventory of empty skips for rental. Skip rental companies are required to assign vehicles to the recycling facilities indexed by $\mathcal{V}$ at the beginning of each day t in the planning horizon $\mathcal{T}$ for later use of pick and delivery of the skips in accordance with the service requirements.

Based on the operational requirements described above, to model the decision-making process, we define the binary decision variable $z_{v,m,t}$, which indicates whether vehicle m is assigned to recycling facility v on day t. The vehicle assignments are governed by the following constraints:

$$\sum_{v \in \mathcal{V}} z_{v,m,t} \leq 1 \quad \forall m \in \mathcal{M}, t \in \mathcal{T}, \tag{5.1a}$$

$$\sum_{m \in \mathcal{M}} z_{v,m,t} \leq C_v \quad \forall v \in \mathcal{V}, t \in \mathcal{T}, \tag{5.1b}$$

$$z_{v,m,t} \leq f_{m,t} \quad \forall v \in \mathcal{V}, m \in \mathcal{M}, t \in \mathcal{T}, \tag{5.1c}$$

$$f_{m+1,t} \leq f_{m,t} \quad \forall m \in \mathcal{M}, t \in \mathcal{T}. \tag{5.1d}$$

$$z_{v,m,t}, f_{m,t} \in \{0, 1\} \quad \forall v \in \mathcal{V}, m \in \mathcal{M}, t \in \mathcal{T}, \tag{5.1e}$$

Constraint (5.1a) ensures that each vehicle can be assigned to at most one recycling facility per day. Constraint (5.1b) limits the number of vehicles assigned to each recycling facility $v \in \mathcal{V}$, ensuring that it does not exceed a predetermined value C_v. Constraints (5.1c) and (5.1d) model vehicle usage. Specifically, the binary variable $f_{m,t}$ indicates whether vehicle m is used during period t, and Constraint (5.1c) ensures that a vehicle can only be assigned to a recycling facility if it has been used. Constraint (5.1d) is an asymmetric precedence constraint, as all vehicles are assumed to be homogeneous; vehicle $m + 1$ can only be used if vehicle m has been used. This constraint can be omitted if heterogeneous vehicles are considered. Constraint (5.1e) defines the types of variables.

Building on the assignment scheme between vehicles and recycling facilities, we now focus on the specific pickup and delivery decisions for skips in a demand-responsive manner. Specifically, trucks are tasked with serving two types of skip locations: (1) those requiring the rental and delivery of an empty skip, and (2) those requiring the collection of skips at the end of their rental period. For each location i, w.l.o.g., we assume that K_i empty skips are required within the planning horizon. For each skip demand $k \in 1, \ldots, K_i$, the demand must be fulfilled on a specific day within the time interval $\mathcal{T}_k^i$. Each skip has an associated rental period, denoted by δ_i^k, and its collection must occur at the end of this rental period.

For each day t, since each vehicle is assigned to one facility and can carry only one skip at a time, we conclude that the operational scheme for a vehicle consists of three fundamental types of operations (as shown in Figure 5.1), listed below:

- Type 1 (binary variable $x^1_{i,m,t}$): Truck m delivers an empty skip to location i and returns to the recycling facility. This operation serves locations with a demand for empty skips. Figure 5.1 illustrates this process at Location 1, where the truck arrives to drop off an empty skip.
- Type 2 (binary variable $x^2_{i,m,t}$): Truck m collects a skip at its end of rental period from location i and returns to the recycling facility. This operation involves picking up skips at its end of rental period ready for collection. Figure 5.1 depicts this process at Location 2, where the truck arrives to collect a waste-filled skip.
- Type 3 (binary variable $y_{i,j,m,t}$): Truck m delivers an empty skip to location i, then proceeds to collect a skip at its end of rental period from location j before returning to the recycling facility. This dual operation addresses both delivery and collection needs in a single trip. Figure 5.1 illustrates this process at Location 3, where the truck exchanges a a skip at its end of rental period for an empty one.

Given the three fundamental operations defined above, we can model the pickup and delivery decisions of trucks as follows:

Pickup and delivery constraints

$$\sum_{i\in\mathcal{I}}(x^1_{i,m,t}+x^2_{i,m,t})+\sum_{i,j\in\mathcal{I}}y_{i,j,m,t}\leq M\sum_{v\in\mathcal{V}}z_{v,m,t}\quad\forall m\in\mathcal{M},t\in\mathcal{T},\tag{5.2a}$$

$$\sum_{m\in\mathcal{M}}\big(x^1_{i,m,t}+x^2_{i,m,t}+\sum_{j\in\mathcal{I}}y_{i,j,m,t}+\sum_{j\in\mathcal{I}/\{i\}}y_{j,i,m,t}\big)\leq 1\quad\forall i\in\mathcal{I},t\in\mathcal{T},\tag{5.2b}$$

$$\sum_{t\in\mathcal{T}^i_k}\big(\sum_{m\in\mathcal{M}}x^1_{i,m,t}+\sum_{m\in\mathcal{M}}\sum_{j\in\mathcal{I}}y_{i,j,m,t}\big)=1\quad\forall i\in\mathcal{I},k\in\{1,\ldots,K_i\},\tag{5.2c}$$

$$\sum_{m\in\mathcal{M}}x^1_{i,m,t}+\sum_{m\in\mathcal{M}}\sum_{j\in\mathcal{I}}y_{i,j,m,t}\leq d_{i,t}\quad\forall i\in\mathcal{I},t\in\mathcal{T},\tag{5.2d}$$

$$q_{i,t}=\sum_{m\in\mathcal{M}}\big(\sum_{j\in\mathcal{I}}y_{i,j,m,t-\delta^k_i}+x^1_{i,m,t-\delta^k_i}\big)\quad\forall i\in\mathcal{I},t\in\mathcal{T},\tag{5.2e}$$

$$\sum_{m\in\mathcal{M}}x^2_{i,m,t}+\sum_{m\in\mathcal{M}}\sum_{j\in\mathcal{I}}y_{j,i,m,t}=q_{i,t}\quad\forall i\in\mathcal{I},t\in\mathcal{T},,\tag{5.2f}$$

$$x^1_{i,m,t},x^2_{i,m,t},q_{i,t}\in\{0,1\}\quad\forall i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T},,\tag{5.2g}$$

$$y_{i,j,m,t}\in\{0,1\}\quad\forall i,j\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T},\tag{5.2h}$$

Constraints (5.2a) to (5.2h) delineate the feasible region for vehicle pickup and delivery decisions. Constraint (5.2a) ensures that a truck $m\in\mathcal{M}$ can serve C&D waste generation locations only if it is assigned to a recycling facility. Constraint (5.2b) specifies that the demand at each C&D waste generation location on any day t must be met through one of the three fundamental operations defined earlier, performed by a truck. Constraint (5.2c) captures the servicing requirements for C&D waste generation locations needing empty skips. For each location i, it is assumed that K_i empty skip deliveries are required within the planning horizon. Each delivery k must occur within the specified time interval $\mathcal{T}^i_k$. Constraint (5.2d) ensures that empty skips can only be delivered to C&D waste generation locations on designated days, represented by the parameter $d_{i,t}$, which equals 1 if $t\in\mathcal{T}^i_k$ for some $k\in 1,\ldots,K_i$ and 0 otherwise. Constraint (5.2e) defines that a delivered empty skip will need to be collected δ^k_i days, coinciding with the end of its rental period. The binary variable $q_{i,t}$ indicates whether a skip at location i is at the end of its rental period on day t. According to Constraint (5.2f), skips at the end of rental period must be collected by a vehicle. Lastly, Constraints (5.2g) and (5.2h) define the types of variables used in the formulation.

Table 5.1. Notation and description

Notation	Description
$\mathcal{M}$	Set of vehicles
$\mathcal{T}$	Set of days
$\mathcal{V}$	Set of recycling facilities and truck depots
$\mathcal{I}$	C&D waste generation locations
$z_{v,m,t}$	Binary variable: 1 if vehicle m is assigned to recycling facility v on day t, 0 otherwise
$x^1_{i,m,t}$	Binary variable: 1 if truck m deliver an empty skip is delivered to location i and directly return to the depot on day t, 0 otherwise
$x^2_{i,m,t}$	Binary variable: 1 if truck m pickup a skip at its end of rental period from location i and return to the depot on day t, 0 otherwise
$y_{i,j,m,t}$	Binary variable: 1 if a truck m deliver an empty skip to location i and then subsequently pickup a a skip at its end of rental period from location j and returns to recycling facility on day t, 0 otherwise
$f_{m,t}$	Binary variable: 1 if vehicle m is used on day t, 0 otherwise
$q^2_{i,t}$	Binary variable: 1 if location i has a skip at its end of rental period to be picked up on day t, 0 otherwise
c_m	Parameter: cost of using vehicle m
$l_{i,v}$	Parameter: Round trip travel cost between location i and recycling facility v
$l_{i,j,v}$	Parameter: Travel cost of the sequence $\{v, i, j, v\}$ considered in the third-type operation, i.e., from recycling facility v to location i, then to location j, and back to recycling facility v
$d_{i,t}$	Binary parameter: 1 if location i potentially needs an empty skip on day t, 0 otherwise
$\mathcal{T}^i_k$	Set of days in period k for skip i
K_i	Number of requirement for empty skip for location i
δ^k_i	Number of days it takes for skip i to fill up
D	Maximum allowed travel hours for a vehicle in a day

Table 5.2. Uncertainty model notation and description

Notation	Description
Vanilla Uncertainty Model	
$\tilde{\tau}_{i,j}$	Random variable representing uncertain travel time between i and j
$\tau^s_{i,j}$	Travel time between i and j in scenario s
$\mathcal{S}$	Set of scenarios
$\Phi^s_{m,t}$	Binary variable: 1 if scenario s is selected for vehicle m on day t, 0 otherwise
S	Total number of scenarios
M_s	Large constant for big-M formulation with sample s
Robustness Uncertainty Model	
$\tau^*_{i,j}$	Adjusted travel time between i and j
$\mu_{i,j}$	Mean travel time between i and j
$\overline{\tau}_{i,j}$	Upper bound of travel time between i and j
$\underline{\tau}_{i,j}$	Lower bound of travel time between i and j
$\sigma_{i,j}$	Standard deviation of travel time between i and j
ϵ	Parameter controlling the level of conservatism

In summary, Constraints (5.1a)–(5.1e) depict the assignment of vehicles, and Constraints (5.2a)–(5.2h) model the pickup and delivery strategies. Then, with the objective to minimizing the total operation cost, which consists vehicle usage cost and traveling cost, we present the formulation of the model as follows:

$$\min \sum_{m\in\mathcal{M}}\sum_{t\in\mathcal{T}} c_m f_{m,t}$$
$$+ \sum_{m\in\mathcal{M}}\sum_{t\in\mathcal{T}}\sum_{v\in\mathcal{V}}\Big(\sum_{i\in\mathcal{I}} l_{i,v} z_{v,m,t}(x^1_{i,m,t}+x^2_{i,m,t})$$
$$+ \sum_{i,j\in\mathcal{I}} l_{i,j,v} y_{i,j,m,t} z_{v,m,t}\Big), \tag{5.3a}$$

s.t. (5.1a)–(5.1e),(5.2a)–(5.2h),

$$f_{m,t}(\boldsymbol{x},\boldsymbol{y},z,\tilde{\boldsymbol{\tau}}) \le D \quad \forall m\in\mathcal{M}, t\in\mathcal{T}, \tag{5.3b}$$

$$f_{m,t}(\boldsymbol{x},\boldsymbol{y},z,\tilde{\boldsymbol{\tau}}) = \sum_{v\in\mathcal{V}} z_{v,m,t}\Big(\sum_{i\in\mathcal{I}} \tilde{\tau}_{i,v}(x^1_{i,m,t}+x^2_{i,m,t}) \tag{5.3c}$$
$$+ \sum_{i,j\in\mathcal{I}} \tilde{\tau}_{i,j,v} y_{i,j,m,t}\Big) \;\forall m\in\mathcal{M}, t\in\mathcal{T}.$$

objective (5.3a), the total operation cost consists of two components: the vehicle usage cost and the travel cost incurred during the planning horizon. Here c_m denote the usage cost of vehicle m, $l_{i,v}$ denote the round trip travel costs between i and v, $l_{i,j,v}$ denote the cost that travels along the sequence $\{v,i,j,v\}$.Vehicle assignment, as well as pickup and delivery decisions, are modeled through Constraints (5.1a)–(5.1e) and (5.2a)–(5.2h). Constraint (5.3b) stipulates that the total working time for each vehicle m on day t cannot exceed its working time limit, denoted by D. This is modeled by summing the travel times associated with the three types of operations defined earlier, where $\tilde{\tau}_{i,v}$ is the round trip travel time between i and v, and $\tilde{\tau}_{i,j,v}$ denote the travel time of the sequence $\{v,i,j,v\}$ by the definition of the third-type pickup and delivery operation ($y_{i,j,m,t}$). Problem (5.3a) is a mixed-integer programming model involving binary terms (such as $z_{v,m,t}x^1_{i,m,t}$, $z_{v,m,t}x^2_{i,m,t}$), which can be linearized using Big-M methods or directly handled by commercial solvers like Gurobi.

Problem (5.3a) presents the MIP formulation of the skip operation problem, in which the travel-time $\tilde{\boldsymbol{\tau}}$ is considered as a deterministic parameter. However, in practice, it is common that the travel-time is uncertain due to reasons such as traffic congestion. The uncertainties of travel time may lead to the realized travel-time for a vehicle m exceeding its threshold D. Thus, from a risk-averse perspective, we will discuss in next section about the uncertain formulation of the model we considered.

5.4.2 Distributionally robust models

To account for uncertainties in travel times, it is common to use a chance-constraint to ensure that the violation of the threshold is minimized as follows:

$$\mathbb{P}\big(f_{m,t}(\boldsymbol{x}, \boldsymbol{y}, z, \tilde{\boldsymbol{\tau}}) \leq D\big) \geq 1 - \epsilon. \tag{5.4}$$

Here, $\mathbb{P}$ is the distribution that governs $\tilde{\boldsymbol{\tau}}$, and the satisfying probability of the constraint is required to be larger than $1 - \epsilon$ by Constraint (5.4). Yet, in the real world, we cannot observe $\mathbb{P}$. What may be available are the historical data, from which one can generate an empirical distribution to approximate the true one. A common model that utilizes historical data is empirical optimization, which resembles the sample average approximation technique commonly used in a stochastic program. Specifically, one often use the Constraints (5.5a) and (5.5b):

$$\frac{1}{S}\sum_{s=1}^{S} \phi_{m,t}^{s} \geq 1 - \epsilon \quad \forall m \in \mathcal{M}, t \in \mathcal{T}, \tag{5.5a}$$

$$f_{m,t}(\boldsymbol{x}, \boldsymbol{y}, z, \boldsymbol{\tau}_s) - M_s(1 - \phi_{m,t}^{s}) \leq D \quad \forall m \in \mathcal{M}, t \in \mathcal{T}, \tag{5.5b}$$

In Constraints (5.5a) and (5.5b), a series of samples indexed by $s \in \{1, \ldots, S\}$ is incorporated, which can be obtained from historical travel-time data observed previously. In Constraint (5.5a), an auxiliary binary variable $\phi_{m,t}^{s}$ is introduced, which equals 1 if $f_{m,t}(\boldsymbol{x}, \boldsymbol{y}, z, \boldsymbol{\tau}_s) \leq D$, and 0 otherwise. The chance-constraint is approximated by the number of samples that satisfy the inequality $f_{m,t}(\boldsymbol{x}, \boldsymbol{y}, z, \boldsymbol{\tau}_s) \leq D$. The value of $\phi_{m,t}^{s}$ is ensured by Constraint (5.5b), where $\phi_{m,t}^{s}$ equals 1 if the inequality is satisfied, and equals 0 to make the constraint redundant (with M_s being a sufficiently large positive value) when $f_{m,t}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{\tau}_s) > D$.

Constraints (5.5a) and (5.5b) can be recast as a mixed-integer linear optimization model that is solvable via state-of-the-art solvers. Yet, it is essentially an approximation approach, and a good approximation requires a large number of samples, which poses computational challenges and is subject to data availability. Moreover, When data are limited, the empirical distribution does not well approximate the true distribution; thus, the empirical optimization may not perform well. A common approach to address distributional ambiguity is the DRO method [Delage and Ye, 2010, Bertsimas et al., 2019]. The DRO method does not rely on a specific distribution but instead assumes that the true distribution lies within an ambiguity set. This approach has demonstrated strong robustness and out-of-sample performance across numerous applications [Ghosal and Wiesemann, 2020, Shehadeh, 2023, Li et al., 2024].

Therefore, we adopt the DRO approach to model the chance-constraint, using an ambiguity set $\mathcal{F}$ to represent the possible distributions of the uncertain parameters, and present the chance-constraints as follows:

$$\begin{aligned} & \mathbb{P}\big(f_{m,t}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \tilde{\boldsymbol{\tau}}) \leq D\big) \geq 1 - \epsilon \quad \forall \mathbb{P} \in \mathcal{F} \\ \iff & \sup_{\mathbb{P} \in \mathcal{F}} \mathbb{P}\text{-VaR}_{1-\epsilon}[f_{m,t}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \tilde{\boldsymbol{\tau}})] \leq D. \end{aligned} \tag{5.6}$$

Here, VaR is the value-at-risk of a random variable, defined as:

$$\mathbb{P}\text{-VaR}_{1-\epsilon}[\tilde{\omega}] := \inf\{a \in \mathbb{R} : \mathbb{P}[\tilde{\omega} \leq a] \geq 1 - \epsilon\},$$

which is the $(1 - \epsilon)$-quantile of the random variable $\tilde{\omega}$.

Note that the specific formulation of the ambiguity set has not yet been defined. Typically, one may use moment information derived from historical data to construct the ambiguity set, such as $\mathcal{F}_1$:

$$\mathcal{F}_1 = \left\{ \mathbb{P} \in \mathcal{P}(\mathbb{R}^{|\tilde{\boldsymbol{\tau}}|}) \left| \begin{array}{c} \tilde{\boldsymbol{\tau}} \sim \mathbb{P} \\ \mathbb{E}_{\mathbb{P}}\left[\tilde{\boldsymbol{\tau}}\right] = \boldsymbol{\mu} \\ \mathbb{E}_{\mathbb{P}}\left[|\tilde{\boldsymbol{\tau}} - \boldsymbol{\mu}|\right] \leq \boldsymbol{\sigma} \\ \mathbb{P}[\tilde{\boldsymbol{\tau}} \in \mathcal{D}] = 1 \end{array} \right. \right\},$$

Here, $\mathbb{E}_{\mathbb{P}}[\cdot]$ stands for the expectation of uncertain parameters, $\mathcal{D}$ is the support set defined as $\mathcal{D} := \left\{\tilde{\boldsymbol{\tau}} \in \mathbb{R}^{|\tau|} \middle| \underline{\boldsymbol{\tau}} \leq \tilde{\boldsymbol{\tau}} \leq \overline{\boldsymbol{\tau}}\right\}$. The first and the third constraints define the mean and support of the uncertain factors. The second constraint provides an upper bound for the mean absolute deviation, denoted by $\boldsymbol{\sigma}$, which provides a direct measure of the uncertainty's dispersion from its mean value $\boldsymbol{\mu}$. Thus, the mean absolution deviation plays a similar role to the standard deviation. For example, in a normal distribution, the ratio between the mean absolute deviation and the standard deviation is $\sqrt{2/\pi}$. And for the uniform distribution on [0,1], that ratio is equal to $\sqrt{3}/2$. Such an ambiguity set has been widely applied in operations such as humanitarian logistics, healthcare delivery, and surgery scheduling [Shehadeh, 2023, Cui et al., 2023, Wang et al., 2023, Li et al., 2024], and demonstrates good tractability due to its structure.

Given ambiguity set $\mathcal{F}_1$, because it is only composed by marginal information on the vector $\tilde{\boldsymbol{\tau}}$, and based on the analytical results of [Ghosal and Wiesemann, 2020], we can reformulate the Constraint (5.6) by Proposition 5.1.

Proposition 5.1. *Let $\mathcal{F}_1$ denote the ambiguity set in which, for each (i, v) and (i, j, v), the random travel times have known mean μ, variance σ^2, and (optional) support $[\underline{\tau}, \overline{\tau}]$, and let $f_{m,t}$ be affine in these travel-time variables. Then the distributionally robust chance constraint* (5.6) *is (safely) enforced by*

$$\sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{I}} \tau^*_{i,v}\, z_{v,m,t}\big(x^1_{i,m,t} + x^2_{i,m,t}\big) \;+\; \sum_{v\in\mathcal{V}}\sum_{i,j\in\mathcal{I}} \tau^*_{i,j,v}\, y_{i,j,m,t} \;\leq\; D, \tag{5.7}$$

where

$$\tau^*_{i,v} := \mu_{i,v} + \min\left\{ \overline{\tau}_{i,v} - \mu_{i,v},\ \frac{1-\epsilon}{\epsilon}\,(\mu_{i,v} - \underline{\tau}_{i,v}),\ \sigma_{i,v}\sqrt{\frac{1-\epsilon}{\epsilon}} \right\},$$

$$\tau^*_{i,j,v} := \mu_{i,j,v} + \min\left\{ \overline{\tau}_{i,j,v} - \mu_{i,j,v},\ \frac{1-\epsilon}{\epsilon}\,(\mu_{i,j,v} - \underline{\tau}_{i,j,v}),\ \sigma_{i,j,v}\sqrt{\frac{1-\epsilon}{\epsilon}} \right\}.$$

If $\mathcal{F}_1$ is componentwise and $f_{m,t}$ is affine, the reformulation is exact for the worst-case one-sided quantiles; otherwise it is a valid conservative approximation.

PROOF. See the proof detail in Appendix A □

The ambiguity set $\mathcal{F}_1$ is constructed based on the marginal information of the mean absolute deviation of travel times. Additionally, one can also choose to construct an ambiguity set based on the variance of the travel times, such as the ambiguity set $\mathcal{F}_2$:

$$\mathcal{F}_2 = \left\{ \mathbb{P} \in \mathcal{P}(\mathbb{R}^{|\tilde{\tau}|}) \;\middle|\; \begin{array}{c} \tilde{\boldsymbol{\tau}} \sim \mathbb{P} \\ \mathbb{E}_{\mathbb{P}}\left[\tilde{\boldsymbol{\tau}}\right] = \boldsymbol{\mu} \\ \mathbb{E}_{\mathbb{P}}\left[(\tilde{\tau}_{i,v} - \mu_{i,v})^2\right] \le \sigma_{i,v}\ \forall i \in \mathcal{I}, v \in \mathcal{V} \\ \mathbb{E}_{\mathbb{P}}\left[(\tilde{\tau}_{i,j,v} - \mu_{i,j,v})^2\right] \le \sigma_{i,j,v}\ \forall i,j \in \mathcal{I}, v \in \mathcal{V} \\ \mathbb{P}[\tilde{\boldsymbol{\tau}} \in \mathcal{D}] = 1 \end{array} \right\},$$

$\mathcal{F}_2$ differs from $\mathcal{F}_1$ by using the variance instead of the mean absolute deviation that was previously used. In a similar manner, the distributionally robust chance-constraint (5.6) can be equivalently reformulated, as shown in Corollary 5.1.

COROLLARY 5.1. *Under the ambiguity set defined by $\mathcal{F}_2$, the distributionally robust chance-constraint* (5.6) *is equivalent to:*

$$\sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{I}} \tau^*_{i,v} z_{v,m,t}(x^1_{i,m,t} + x^2_{i,m,t}) + \sum_{v\in\mathcal{V}}\sum_{i,j\in\mathcal{I}} \tau^*_{i,j,v} y_{i,j,m,t} \le D \tag{5.8}$$

where $\tau^*_{i,j} = \mu_{i,v} + \min\{\overline{\tau}_{i,v} - \mu_{i,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,v} - \underline{\tau}_{i,v}), \sqrt{\frac{1-\epsilon}{\epsilon}}\sigma_{i,v}\}$ *and* $\tau^*_{i,j,v} := \mu_{i,j,v} + \min\{\overline{\tau}_{i,j,v} - \mu_{i,j,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,j,v} - \underline{\tau}_{i,j,v}), \sqrt{\frac{1-\epsilon}{\epsilon}}\sigma_{i,j,v}\}$.

Proof sketch. Let

$$S := \sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{I}} \tau_{i,v}\, z_{v,m,t}\big(x^1_{i,m,t} + x^2_{i,m,t}\big) + \sum_{v\in\mathcal{V}}\sum_{i,j\in\mathcal{I}} \tau_{i,j,v}\, y_{i,j,m,t},$$

where each uncertain travel time has marginal information $\mu_{i,v}, \sigma_{i,v}, [\underline{\tau}_{i,v}, \overline{\tau}_{i,v}]$ and $\mu_{i,j,v}, \sigma_{i,j,v}, [\underline{\tau}_{i,j,v}, \overline{\tau}_{i,j,v}]$, as specified by the ambiguity set $\mathcal{F}_2$. The distributionally robust chance constraint in (5.6) is equivalent to

$$\sup_{P\in\mathcal{F}_2} \mathrm{VaR}_{1-\epsilon}(S) \le D,$$

since $\mathrm{VaR}_{1-\epsilon}$ is the smallest threshold whose exceedance probability is at most ϵ.

Step 1 (Worst-case dependence is comonotone). All decision coefficients that multiply uncertain times are nonnegative (e.g., $z_{v,m,t} \in \{0,1\}$, $y_{i,j,m,t} \ge 0$). Hence S is coordinatewise nondecreasing in every uncertain component. Because $\mathcal{F}_2$ places no constraints on dependence, the worst-case (largest) upper-tail/quantile of such a sum is attained by a *comonotone* coupling of the marginals. For comonotone random variables and nonnegative weights,

$$\mathrm{VaR}_{1-\epsilon}\left(\sum_k c_k X_k\right) = \sum_k c_k\ \mathrm{VaR}_{1-\epsilon}(X_k).$$

Therefore,

$$\sup_{P\in\mathcal{F}_2} \mathrm{VaR}_{1-\epsilon}(S) = \sum_{v,i} z_{v,m,t}\big(x^1_{i,m,t} + x^2_{i,m,t}\big)\,\theta^*_{i,v} + \sum_{v,i,j} y_{i,j,m,t}\,\theta^*_{i,j,v},$$

where θ^* is the worst-case $(1-\epsilon)$-quantile of each scalar marginal under its own $(\mu, \sigma, \text{support})$ information.

Step 2 (Worst-case scalar quantile under $\mathcal{F}_2$). Fix a scalar X with mean μ, variance σ, and support $[\underline{\tau}, \overline{\tau}]$. Its worst-case $(1-\epsilon)$-quantile q^* is the smallest s such that $\sup_{P\in\mathcal{F}_2} \mathbb{P}(X > s) \le \epsilon$. Three tight one-sided bounds yield an envelope for q^*:

$$\begin{aligned}
&\text{(Support)} \quad q^* \le \overline{\tau} \;\; \Rightarrow \;\; q^* - \mu \le \overline{\tau} - \mu, \\
&\text{(Markov on } X - \underline{\tau}) \quad \mathbb{P}(X > s) \le \frac{\mu - \underline{\tau}}{s - \underline{\tau}} \;\Rightarrow\; q^* \le \mu + \frac{1-\epsilon}{\epsilon}(\mu - \underline{\tau}), \\
&\text{(Cantelli/Chebyshev)} \quad \mathbb{P}(X - \mu \ge t) \le \frac{\sigma}{\sigma + t^2} \;\Rightarrow\; q^* \le \mu + \sqrt{\frac{1-\epsilon}{\epsilon}}\,\sigma.
\end{aligned}$$

Each bound is attainable by an extremal (two-point) distribution consistent with $(\mu, \sigma, \underline{\tau}, \overline{\tau})$, so the tight worst-case quantile is

$$q^* \;=\; \mu + \min\left\{ \overline{\tau} - \mu,\; \frac{1-\epsilon}{\epsilon}(\mu - \underline{\tau}),\; \sqrt{\frac{1-\epsilon}{\epsilon}\,\sigma} \right\}.$$

Applying this to every node-time and arc-time variable gives $\theta^*_{i,v} = \tau^*_{i,v} := \mu_{i,v} + \min\{\overline{\tau}_{i,v} - \mu_{i,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,v} - \underline{\tau}_{i,v}), \sqrt{\frac{1-\epsilon}{\epsilon}\sigma_{i,v}}\}$ and $\theta^*_{i,j,v} = \tau^*_{i,j,v} := \mu_{i,j,v} + \min\{\overline{\tau}_{i,j,v} - \mu_{i,j,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,j,v} - \underline{\tau}_{i,j,v}), \sqrt{\frac{1-\epsilon}{\epsilon}\sigma_{i,j,v}}\}$.

Step 3 (Equivalence). Combining Steps 1–2,

$$\sup_{P\in\mathcal{F}_2} \mathrm{VaR}_{1-\epsilon}(S) = \sum_{v,i} \tau^*_{i,v}\, z_{v,m,t}(x^1_{i,m,t} + x^2_{i,m,t}) + \sum_{v,i,j} \tau^*_{i,j,v}\, y_{i,j,m,t}.$$

Thus the DR chance constraint holds iff the deterministic inequality in (5.8) holds, proving the claim. □

Based on the reformulation results above, we can now present our distributionally robust chance-constraint formulation as follows:

$$
\begin{aligned}
\min \sum_{m\in\mathcal{M}} \sum_{t\in\mathcal{T}} & c_m f_{m,t} \\
& + \sum_{m\in\mathcal{M}} \sum_{t\in\mathcal{T}} \sum_{v\in\mathcal{V}} \Big(\sum_{i\in\mathcal{I}} l_{i,v} z_{v,m,t} (x^1_{i,m,t} + x^2_{i,m,t}) \\
& \quad + \sum_{i,j\in\mathcal{I}} l_{i,j,v} y_{i,j,m,t} z_{v,m,t} \Big), \qquad (5.9a) \\
\text{s.t. } & (5.1a)\text{–}(5.1e), (5.2a)\text{–}(5.2h), \\
& \text{DRO chance-constraint: } (5.7) \text{ or } (5.8)
\end{aligned}
$$

The formulation of Problem (5.9a) can be directly solved by commercial solvers such as Gurobi. Practitioners can choose to adopt the mean absolute deviation information through Constraint (5.7) or use the variance information via (5.8), depending on the specific situation they face, such as the availability of data and the performance of these two methods. In the next section, a real case study using data from Sydney, Australia is presented to verify this model, focusing on the performance of its decisions and computational tractability.

5.5 Numerical studies

To evaluate the performance of our models, this section conducts numerical experiments and compares the results of our Distributionally Robust Optimization (DRO-Chance) with benchmark methods, including a Deterministic model and a stochastic programming model with chance constraints (SP-Chance). The evaluation is based on a case study of skip truck operations for C&D waste management in Sydney, Australia . The optimization models were implemented in Python and solved using Gurobi 12.0 on a system featuring a 13th Gen Intel Core i9-13980HX processor.

5.5.1 Case study data and implementation details

We utilized waste generation data from 2023 provided by the New South Wales Environment Protection Authority [NSW Environment Protection Authority, 2024]. Recognizing the strong correlation between population size and waste generation rates [Islam et al., 2019], we collected population data for 30 council areas in Sydney from the Australian Bureau of Statistics [Australian Bureau of Statistics, 2024]. As shown in Figure 5.2, these LGAs constitute the set of waste generation sites, denoted as $\mathcal{I}$, representing the indices of skips in our model. Three LGAs—Wollondilly Shire Council, Hawkesbury City Council, and Blue Mountains City Council—were excluded from $\mathcal{I}$ due to their rural locations and significant distance from the metropolitan area. The selected LGAs account for approximately 95% of Sydney's total population, ensuring a comprehensive representation of the urban waste generation landscape. The total C&D waste generation was proportionally allocated among the LGAs in $\mathcal{I}$ based on their population sizes. Industry consultations indicated that approximately 60% of C&D waste transportation is conducted via skips, the predominant waste management method in Sydney. Using a standard skip capacity of 8 cubic meters, we calculated the skip demand for each LGA $i \in \mathcal{I}$, effectively determining the number of skips required at each location. To efficiently manage the substantial skip demand, we normalized the daily skip demand over a 10-day planning horizon, represented as $\mathcal{T} = \{1, 2, \ldots, 10\}$. Skip rentals operate on a fixed-duration basis: individuals or companies order a skip, which the skip company delivers to the specified site. The skip remains at the location for the agreed rental period—typically ranging from a few days to several weeks—before being collected, regardless of how full it is. the parameter δ_i^k, which denotes the skip rental duration, is set to 3. Consequently, the pickup demand on any given day $t \in \mathcal{T}$ includes skips delivered three days earlier. The set of days in each rental period $\mathcal{T}_k^i$ for skip i is shown as in Table 5.3, which presents the skip demand by council area, showing the days on which skips are required for each LGA. This detailed scheduling allows the model to allocate resources efficiently and meet customer demands. To approximate the

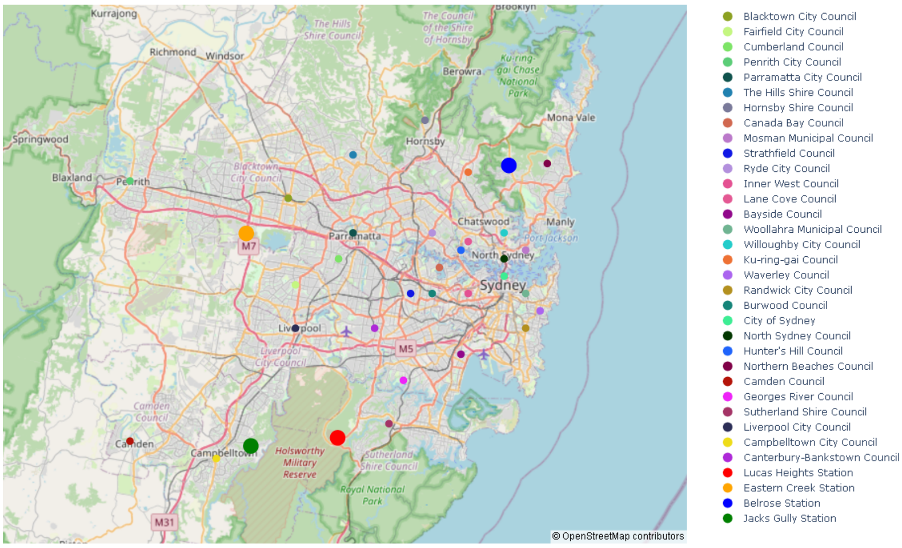


FIGURE 5.2. Geographical distribution of skip demand locations (Council) and waste management facilities & depots (facilities) in Sydney

actual travel distance between destinations, we adjusted the straight-line distance $d_{i,v}$ between skip location i and facilities v by a factor of 1.5, accounting for road network complexities, urban traffic patterns, and potential detours. The distance $d_{i,j,v}$ represents the travel from facilities v to skip i, then to skip j, and back to facilities v. Assuming an average truck speed of 50 km/h, we estimated the travel times by dividing the adjusted distances by 50 km/h. This estimation considers urban speed limits and typical traffic conditions in Sydney. The parameters $\mu_{i,j}$ and $\sigma_{i,j}$ represent the mean and standard deviation of travel times between locations i and j. These parameters are used to model travel time uncertainties due to factors like traffic congestion and roadworks.

To account for variability in computational performance and solution quality, we conducted five simulation runs for each model and configuration. Key performance metrics included the Objective Value (in hours), representing the total operational hours required to service all skip demands over a 10-day period, as well as the Average Solving Time, Maximum and Minimum Solving Times (in seconds), and violation frequency. The violation frequency reflects the model's reliability under uncertainty by indicating the percentage of instances in the out-of-sample test where the solution could not complete the assigned tasks within the designated time constraints.

Experimental protocol (in/out-of-sample). Unless stated otherwise, all models are trained/optimized on an in-sample set of $S = 80$ travel-time scenarios derived from 2023 NSW data (Sec. 5.5). For evaluation, we fix the decisions and assess them on an independent out-of-sample set of $N_{\text{test}} = 1{,}000$ scenarios per instance; violation frequency is the fraction of these out-of-sample scenarios violating time-feasibility. All statistics are averaged over five random seeds.

Model variants used. Unless otherwise noted, **DRO-Chance** solves Problem (5.9a) with the closed-form distributionally robust chance-constraint in Eq. (5.7) (Proposition 5.1). The **SP-Chance** baseline uses the scenario/big-M approximation in Eqs. (5.5a)–(5.5b). The **Deterministic** baseline sets all travel times to their means.

5.5.2 Base model configuration and performance

The baseline configuration for performance analysis consisted of four recycling facilities and skip depots ($v \in \{1, 2, 3, 4\}$), with a service reliability parameter robustness level of $\epsilon = 0.8$. Daily truck operation hours were limited to 10 hours ($D = 10$), and the fixed cost for using a truck per day was equivalent to three hours of operational cost. This standardized setup ensured consistency across tests, allowing the impact of varying parameters to be analyzed in isolation during sensitivity analyses. The detailed task assignment for the base DRO-Chance model is provided in A3. Due to space limitations, we have included detailed results for days two, five, and eleven. These days were selected to capture the variation in operational tasks: during the first three days, operations involve only empty skip drop-offs. From days four through ten, activities expand to include both empty skip drop-offs and pickups of skips whose rental periods have ended. After day ten, operations focus exclusively on retrieving skips due for collection.

The performance of the base model is summarized in Table 5.3, which highlights the key metrics across the Deterministic, SP-Chance, and DRO-Chance models. This baseline serves as a reference point for comparisons in subsequent sensitivity analyses.

Table 5.3. Performance metrics for the base model configuration

Model	**Total Service Time (hrs)**	**Avg. Solving Time (s)**	**Violation Frequency (%)**
Deterministic	264.84	48.29	9.89
SP-Chance	265.78	558.69	7.39
DRO-Chance	269.92	99.03	0.21

The results in Table 5.3 demonstrate the trade-offs among the three models in terms of efficiency, computational time, and reliability. The DRO-Chance model achieves the highest reliability, with a violation frequency of only 0.21%, at the cost of a slightly higher total service time (269.92 hours) compared to the Deterministic (264.84 hours) and SP-Chance (265.78 hours) models. However, this increase in operational cost is offset by the significant reduction in violation frequency, illustrating the robustness of the DRO-Chance model under the baseline configuration.

5.5.3 Analysis of chance constraint robustness level

We vary the service level $1 - \epsilon$ and report all trends versus $1 - \epsilon$ (higher means more conservative). Concretely, we set $\epsilon \in \{0.9, 0.8, 0.7, 0.6, 0.5\}$ so that $1 - \epsilon \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$ increases from 0.1 to 0.5. Figures 5.3 and 5.4 are relabeled using $1 - \epsilon$ on the horizontal axis.

The robustness level ϵ in chance-constraints significantly influences the trade-off between model efficiency, represented by total service time (Objective Value), and reliability, represented by violation frequency. To evaluate these effects, we conducted a sensitivity analysis by varying ϵ (0.9, 0.8, 0.7, 0.6, and 0.5) for the Deterministic, SP-Chance, and

DRO-Chance models. The average results of the analysis are summarized in Table 5.4. Figures 5.3, 5.4, and 5.5 provide graphical insights into the trends across these metrics.

TABLE 5.4. Impact of chance-constraint robustness level ϵ

Robustness Level ϵ	**Model**	**Total Service Time (hrs)**	**Solving Time (s) Avg.**	**Max**	**Min**	**Violation Frequency (%)**
	Deterministic	264.84	52.42	67.13	47.49	9.78
0.9	SP-Chance	266.06	566.16	586.89	549.44	6.77
	DRO-Chance	270.74	55.76	65.59	48.95	0.16
	Deterministic	264.84	48.29	52.04	44.10	9.89
0.8	SP-Chance	265.78	558.69	569.76	548.14	7.39
	DRO-Chance	269.92	99.03	208.14	57.25	0.21
	Deterministic	264.84	46.57	47.96	44.49	9.71
0.7	SP-Chance	265.12	540.64	553.91	526.90	9.86
	DRO-Chance	268.03	59.01	66.84	48.95	2.03
	Deterministic	264.84	55.54	59.18	52.88	9.49
0.6	SP-Chance	265.08	715.11	811.01	578.99	9.71
	DRO-Chance	267.84	71.79	83.83	64.83	2.05
	Deterministic	264.84	48.46	50.79	42.26	9.99
0.5	SP-Chance	265.08	570.14	642.39	499.60	10.02
	DRO-Chance	267.45	68.86	79.04	62.11	3.32

As shown in Figure 5.3, the DRO-Chance model exhibits higher total service times compared to the SP-Chance and Deterministic models across all robustness levels, reflecting its conservative approach to mitigating uncertainty. For instance, at $\epsilon = 0.9$, the DRO-Chance model requires 270.74 hours to service all demands, while the SP-Chance and Deterministic models achieve lower total service times of 266.06 hours and 264.84 hours, respectively. This highlights the additional operational cost incurred by the DRO-Chance model to prioritize reliability.

Conversely, as shown in Figure 5.4, the DRO-Chance model consistently achieves superior reliability, with significantly lower violation frequencies across all robustness levels. At $\epsilon = 0.9$, the DRO-Chance model reduces violation frequency to 0.16%, compared to 6.77% for the SP-Chance model and 9.78% for the Deterministic model. At the lowest robustness level ($\epsilon = 0.5$), the violation frequency for the DRO-Chance model increases

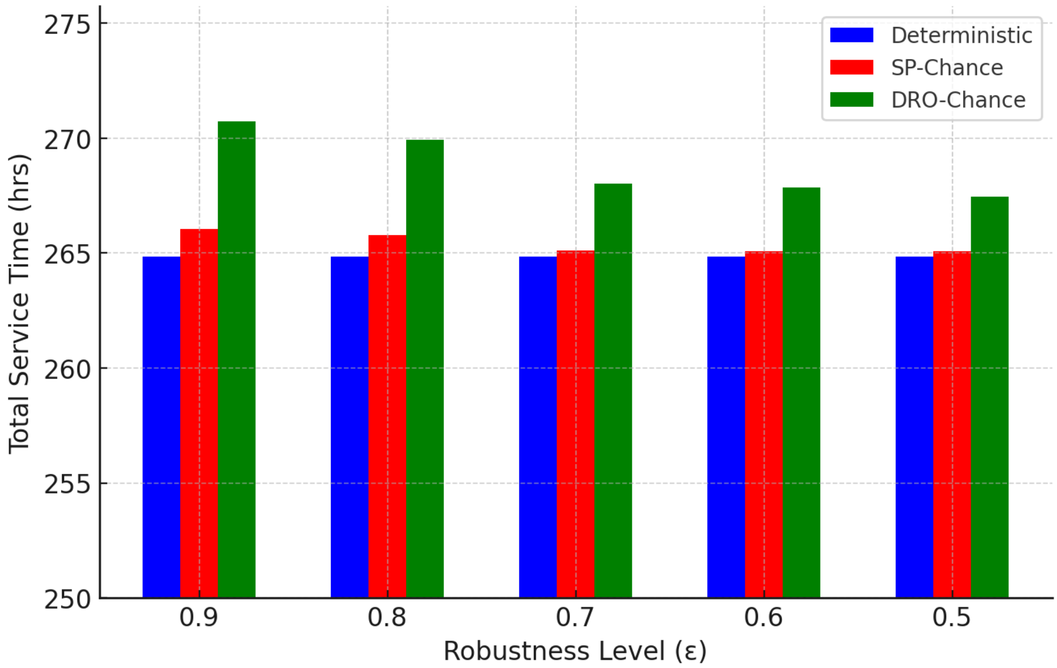


Figure 5.3. Total service time under varying robustness levels

to 3.32%, while the SP-Chance and Deterministic models report much higher freqencies of 10.02% and 9.99%, respectively.

The Price of Robustness for the DRO-Chance model quantifies the efficiency sacrificed to achieve improved reliability. It is calculated using the following formula:

$$\text{Price of Robustness} = \frac{\text{OV(DRO-Chance) - OV(SP-Chance)}}{\text{VF(SP-Chance) - VF(DRO-Chance)}}$$

where OV() and VF() denote the 'Objective Value' (total service time) and the 'violation frequency' of their arguments respectively.

This metric indicates the additional operational hours required per percentage improvement in reliability. For instance, at $\epsilon = 0.9$, the Price of Robustness is 70.80, reflecting the substantial cost of reducing the violation frequency to near-zero levels. At $\epsilon = 0.5$, the Price of Robustness decreases to 35.37, highlighting the diminishing cost associated

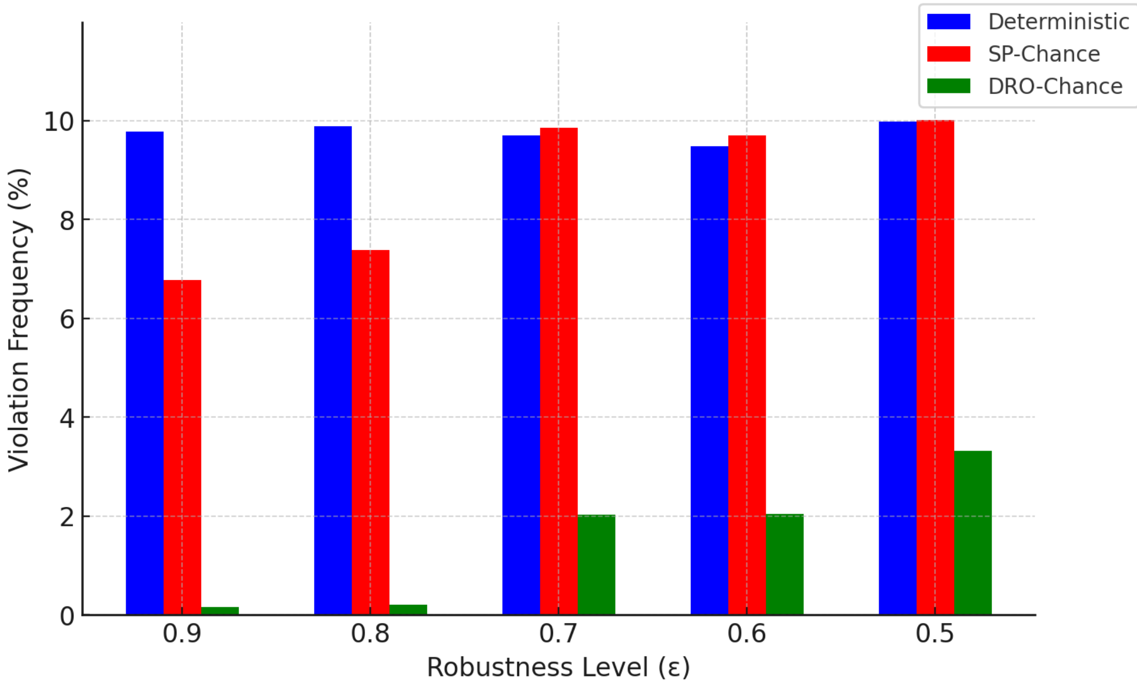


FIGURE 5.4. Violation frequency under varying robustness levels

with less conservative robustness levels. As shown in Figure 5.5, the Price of Robustness decreases as ϵ decreases, demonstrating how the DRO-Chance model balances efficiency and reliability more effectively at lower robustness levels.

The interplay between robustness levels, total service time (Objective Value), violation frequency, and the Price of Robustness provides critical insights for selecting an appropriate robustness level based on operational priorities.

5.5.4 Impact of recycling facilities configuration

The configuration of recycling facilities, represented by the set $\mathcal{V}$ of recycling facilities and truck depots, significantly influences operational efficiency and the system's resilience to uncertainty. To evaluate these impacts, we experimented with varying numbers of recycling facilities—ranging from a single facilities to a four-facilities configuration.

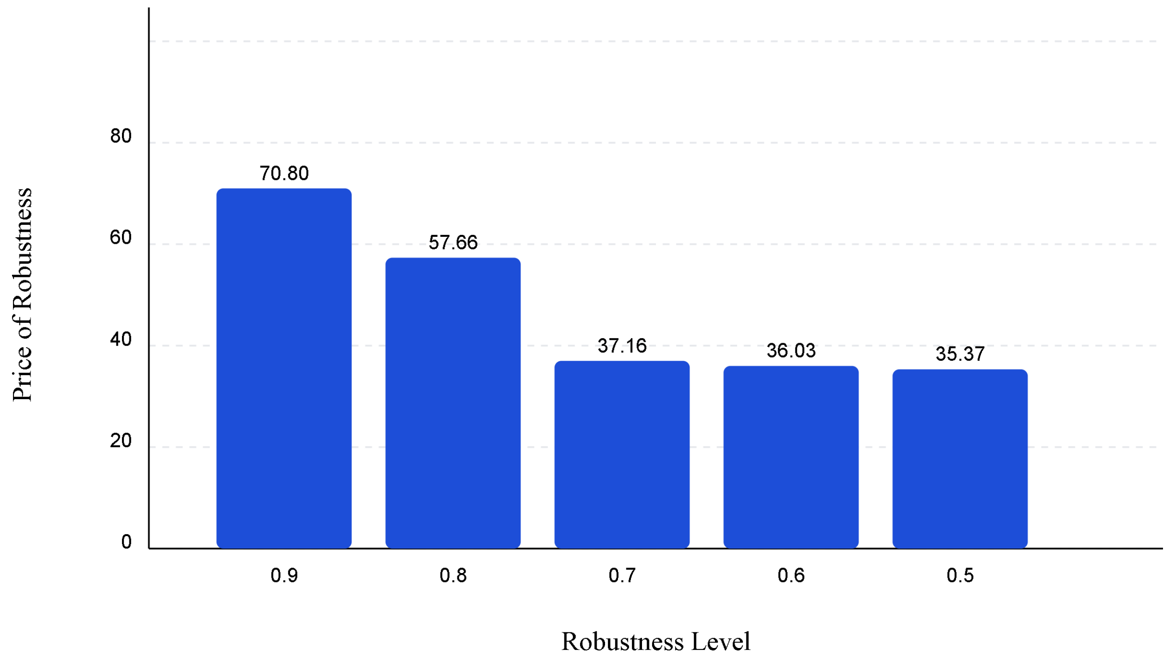


Figure 5.5. Price of robustness under varying robustness levels

Each configuration was tested across the Deterministic, SP-Chance, and DRO-Chance models through five simulation runs, ensuring robustness of the results. The performance metrics include the total service time (objective value in hours required to service skip demands) and violation frequency (percentage of instances where operational constraints were violated). Table 5.5 summarizes these metrics for all configurations.

For the single-facility configuration, Belrose was selected as the recycling facility. In the two-facilities configuration, Belrose and Jacks Gully were chosen. For the three-facilities configuration, Lucas Heights was the only location not selected, leaving Belrose, Jacks Gully, and Eastern Creek as the active facilities. Finally, for the standard four-facilities configuration, all four locations (Belrose, Jacks Gully, Lucas Heights, and Eastern Creek) were included.

Table 5.5 presents the average results, including the Objective Value, which indicates the total number of operational hours required to service all skip demands over the 10-day period. The table also includes the Average Solving Time, Maximum and Minimum Solving Times, and violation frequency for each model and facility configuration.

TABLE 5.5. Performance metrics under different recycling facility configurations

Facilities	Model	Total Service Time (hrs)	Solving Time (s) Avg.	Max	Min	Violation Frequency (%)
One facility	Deterministic	346.21	4.01	4.08	3.91	18.06
	SP-Chance	346.21	110.68	120.95	104.85	18.76
	DRO-Chance	361.21	5.89	6.56	5.22	1.92
Two facilities	Deterministic	294.16	10.32	10.55	10.08	17.11
	SP-Chance	299.93	257.68	266.73	242.38	11.12
	DRO-Chance	319.87	13.20	14.28	12.44	1.03
Three facilities	Deterministic	267.28	25.18	25.87	24.67	13.59
	SP-Chance	269.74	373.82	468.17	332.08	9.24
	DRO-Chance	275.44	26.79	29.94	24.33	0.21
Four facilities	Deterministic	264.84	48.29	52.04	44.10	9.89
	SP-Chance	265.78	558.69	569.76	548.14	7.39
	DRO-Chance	269.92	99.03	208.14	57.25	0.21

As shown in Figure 5.6, the total service time decreases across all models as the number of recycling facilities increases. This trend reflects the improved spatial allocation of resources and shorter travel distances, which allow vehicles to serve skips more efficiently. Notably, the Deterministic model achieves the lowest total service time due to its focus on operational efficiency without considering uncertainty. For example, in the four-facilities configuration, the Deterministic model achieves an total service time of 264.84 hours, the lowest among all models. However, this efficiency comes at the cost of increased vulnerability to operational disruptions.

In contrast, the DRO-Chance model, designed to mitigate the worst-case impact of uncertainty, exhibits slightly higher total service time, such as 361.21 hours in the one-facility configuration and 269.92 hours in the four-facilities configuration. These values highlight the model's conservative approach to handling variability. Despite this trade-off, the DRO-Chance model ensures greater reliability by significantly reducing violation frequencies, as detailed in Figure 5.7.

When it comes to violation frequency, depicted in Figure 5.7, decreases notably as the number of recycling facilities increases. This trend underscores the enhanced resilience provided by higher facility density, which reduces the average travel distance between skip locations and their assigned facilities. For instance, the DRO-Chance model maintains an impressively low violation frequency of 0.21% in both the three- and four-station configurations. This robustness is primarily attributed to the model's ability to anticipate and mitigate worst-case scenarios, further amplified by the reduced variability enabled by a higher facility density.

The SP-Chance model strikes a balance between the Deterministic and DRO-Chance models. While it achieves lower violation frequencies than the Deterministic model, it incurs significantly longer solving times, making it less practical for large-scale operational scenarios.

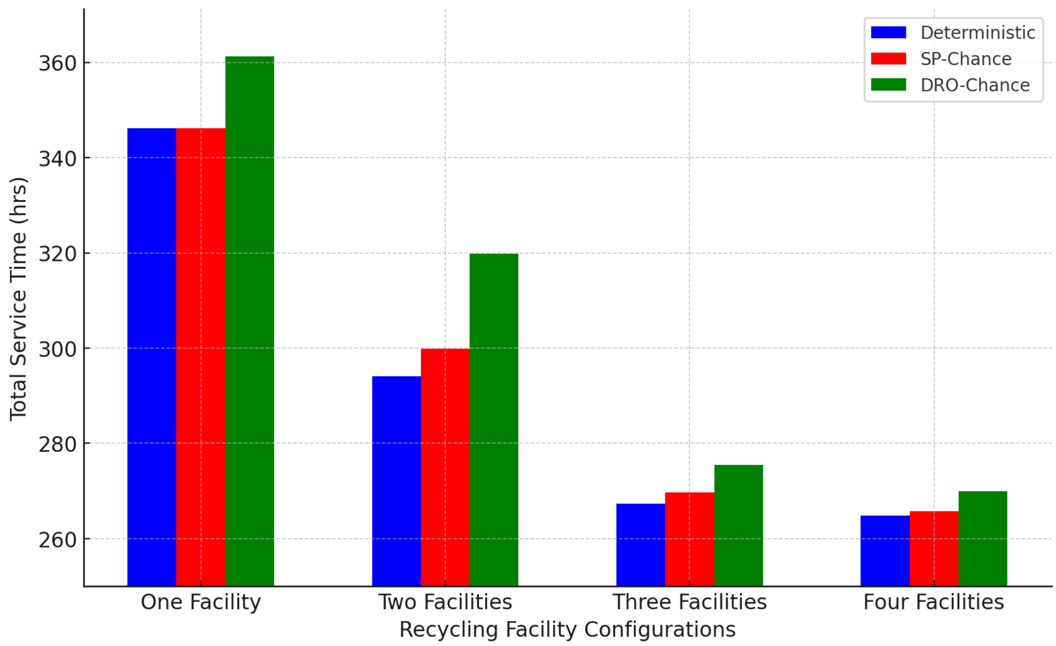


FIGURE 5.6. Total service time under different recycling facility configurations.

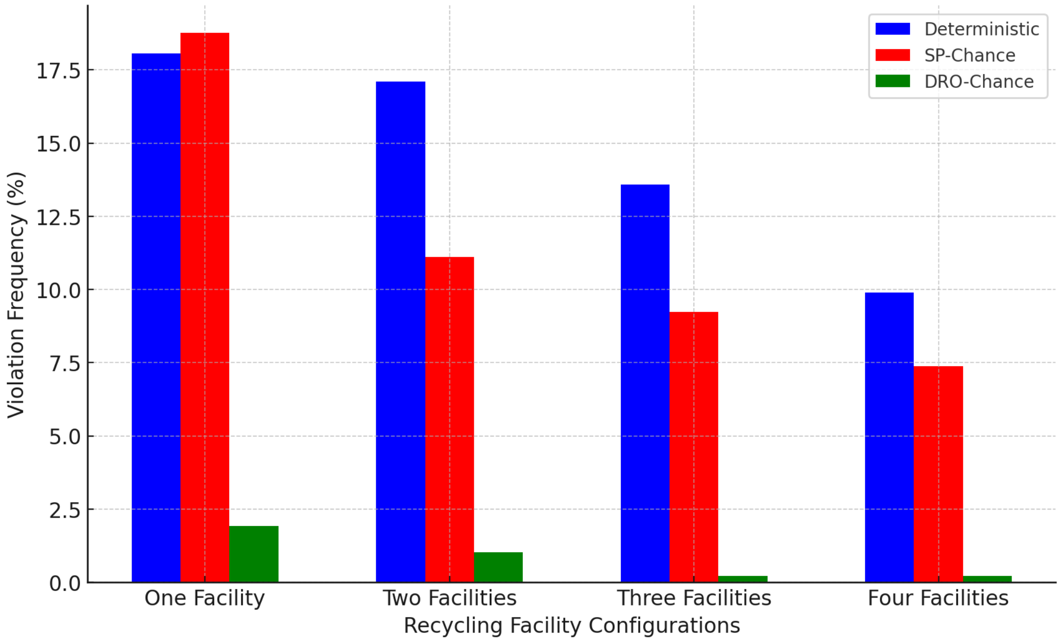


FIGURE 5.7. Violation frequency under different recycling facility configurations

5.5.5 Effect of daily operational time limit

The maximum allowed daily operational time D (in hours) for each vehicle significantly influences both the feasibility of schedules and the models' ability to handle uncertainty. To evaluate these effects, we analyzed the performance of the Deterministic, SP-Chance, and DRO-Chance models under varying daily operational time limits: $D = 9$, $D = 10$, and $D = 11$ hours. Each scenario was simulated five times per model to account for variability in the results. Detailed performance metrics for all scenarios, including total service times (Objective Values) and violation frequencies, are provided in Table 5.6.

Increasing the daily operational time limit, D, provides vehicles with greater flexibility to complete their routes, resulting in reduced violation frequencies and slightly lower total service times (Objective Values). For example, at $D = 11$ hours, the DRO-Chance model achieves a violation frequency of just 0.09% as shown in Figure 5.8, with an total service time of 267.84 hours as illustrated in Figure 5.9. This demonstrates the model's

Table 5.6. Impact of daily operational time limit D

Daily Operational Time D	**Model**	**Total Service Time (hrs)**	**Solving Time (s) Avg.**	**Max**	**Min**	**Violation Frequency (%)**
9 hours	Deterministic	267.84	49.65	52.00	47.15	11.38
	SP-Chance	267.84	488.86	550.30	460.75	11.38
	DRO-Chance	274.22	65.90	78.40	55.25	0.50
10 hours	Deterministic	264.84	48.29	52.04	44.10	9.89
	SP-Chance	265.78	558.69	569.76	548.14	7.39
	DRO-Chance	269.92	99.03	208.14	57.25	0.21
11 hours	Deterministic	264.30	54.59	58.40	50.15	6.99
	SP-Chance	264.55	553.95	566.80	541.50	4.72
	DRO-Chance	267.84	71.34	84.25	61.50	0.09

ability to maintain high reliability while minimizing the total operational hours required. Similarly, the SP-Chance and Deterministic models also benefit from increased daily time limits, with violation freqencies decreasing to 4.72% and 6.99%, respectively, under the same scenario. When $D = 10$ hours, the performance of all models c losely aligns with results observed under the robustness level $P = 0.8$. The DRO-Chance model achieves a violation frequency of 0.21% and an total service time of 269.92 hours, indicating its robust performance even with a moderately constrained daily operational time limit. However, reducing D to 9 hours imposes stricter schedule constraints, leading to increased violation freqencies for all models. The Deterministic and SP-Chance models exhibit violation freqencies of 11.38%, while the DRO-Chance model maintains a significantly lower violation frequency of 0.50%. Despite this reliability, the DRO-Chance model's total service time rises to 274.22 hours, illustrating that stricter operational limits necessitate more total operational hours to meet demand.

5.5.6 Impact of fixed truck cost

We investigated the impact of varying the fixed truck cost c_m (in hours) on performance metrics for the Deterministic, SP-Chance, and DRO-Chance models. Two scenarios were analyzed: c_m equivalent to 3 operational hours and c_m equivalent to 4 operational hours, reflecting higher vehicle overhead costs. For each scenario, we conducted five

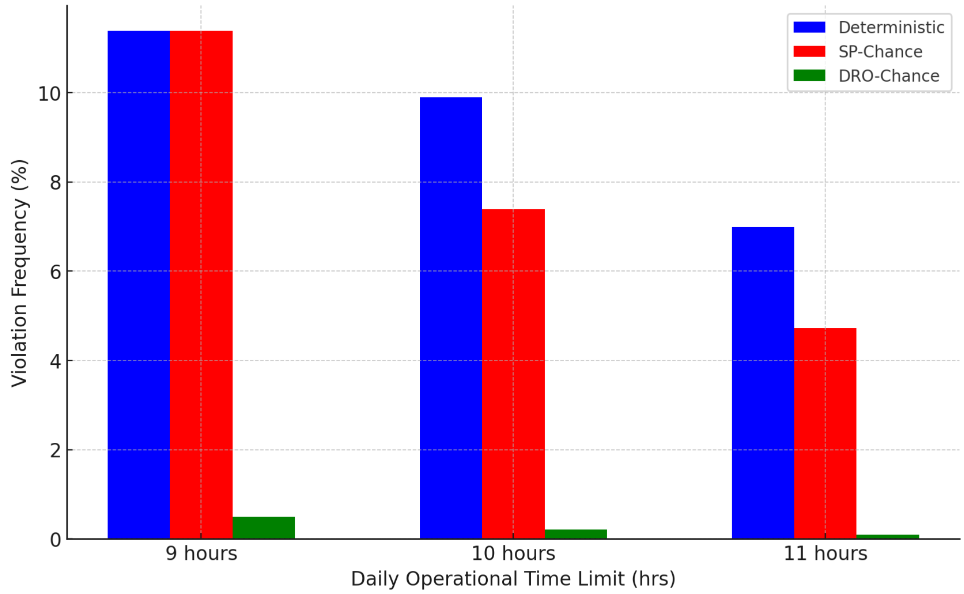


FIGURE 5.8. Violation frequency under different daily operational time limits

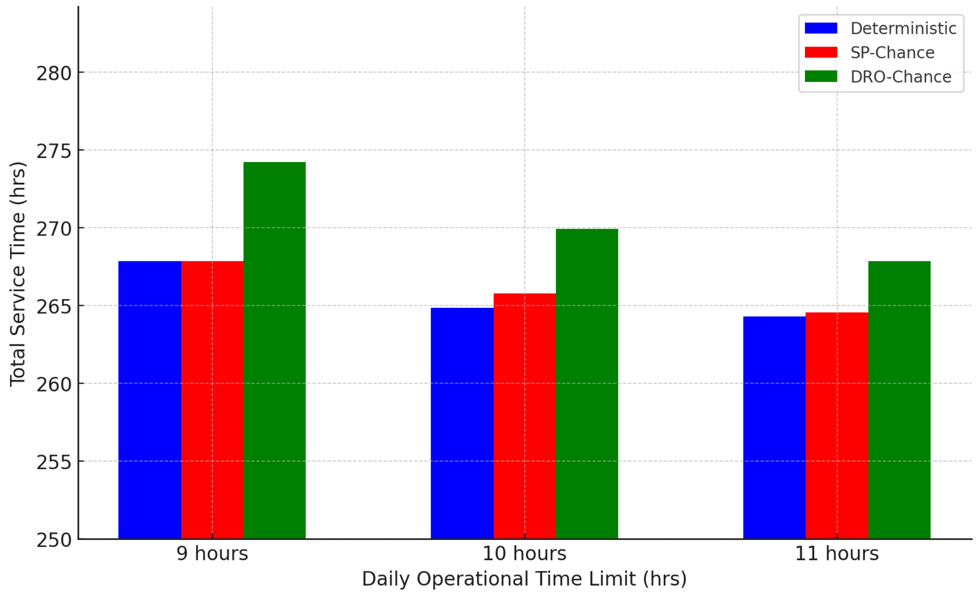


FIGURE 5.9. Total service time under different daily operational time limits

simulations to capture variability in the results. Detailed performance metrics are summarized in Table 5.7.

Table 5.7. Impact of fixed truck cost c_m on performance metrics

Fixed truck cost c_m	**Model**	**Total service time (hrs)**	**Violation Frequency (%)**
3 Hours	Deterministic	264.84	9.89
	SP-Chance	265.78	7.39
	DRO-Chance	269.92	0.21
4 Hours	Deterministic	290.84	9.48
	SP-Chance	291.92	8.35
	DRO-Chance	299.89	0.28

The increased fixed cost c_m results in higher total service times (Objective Values) across all models, as shown in Figure 5.10, indicating that more total operational hours (and thus higher costs) are required to service all skip demands. At $c_m = 4$ hours, the Deterministic model requires 290.84 hours, compared to 264.84 hours at $c_m = 3$ hours. Similarly, the SP-Chance model's total service time increases from 265.78 hours to 291.92 hours, while the DRO-Chance model experiences the highest increase, rising from 269.92 hours to 299.89 hours.

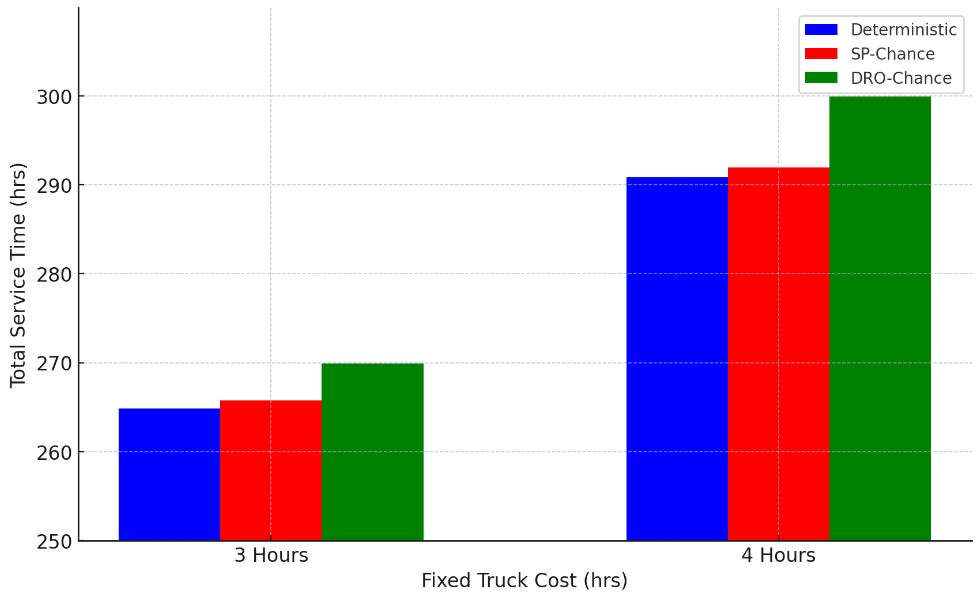


Figure 5.10. Total service time under different fixed truck costs

As depicted in Figure 5.11, violation frequencies generally decrease with increased c_m, particularly for the Deterministic and SP-Chance models. At $c_m = 4$ hours, the Deterministic model's violation frequency decreases slightly to 9.48% from 9.89%, while the SP-Chance model exhibits a similar reduction, from 7.39% to 8.35%. The DRO-Chance model, however, maintains its robustness, with a minimal increase in violation frequency from 0.21% at $c_m = 3$ hours to 0.28% at $c_m = 4$ hours, reflecting its ability to produce reliable solutions despite higher operational costs.

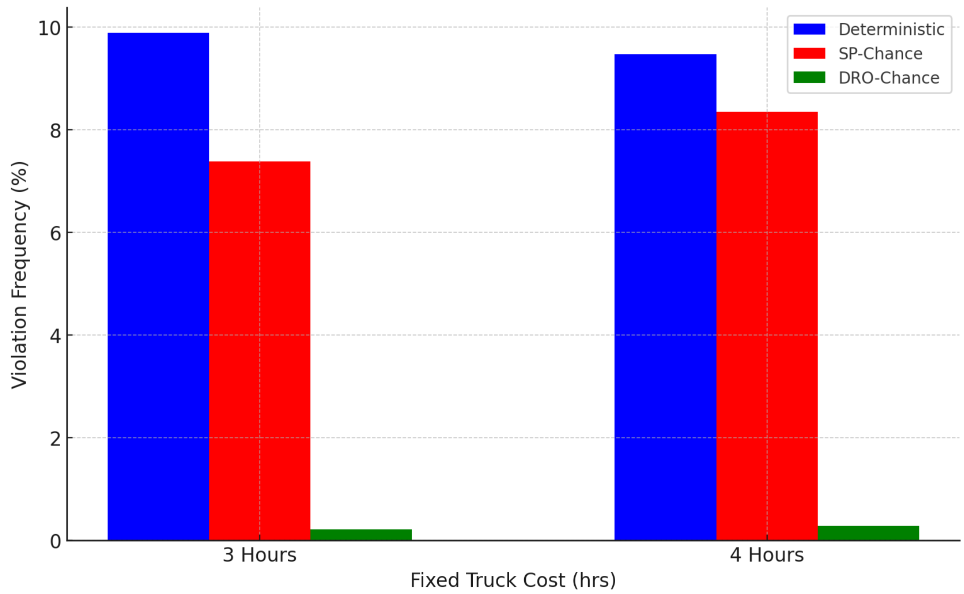


FIGURE 5.11. Violation frequency under different fixed truck costs

5.6 Conclusion

This study has introduced a novel DRO framework to address the demand-responsive skip management problem under travel-time uncertainty, which is commonly seen in practice such as C&D waste management. Our approach explicitly models the unique operational constraints of single-skip vehicles, aligns multiple delivery and pickup tasks over extended rental durations, and incorporates robust methodologies to handle unpredictable travel conditions. By adopting this approach, we introduce a realistic, adaptive, and cost-effective planning tool for urban waste management.

Numerical experiments, grounded in real-world data from the Sydney metropolitan area, confirmed the practical efficacy of our model. Compared to deterministic and stochastic programming baselines, the proposed DRO-based approach consistently achieved lower violation frequencies and improved operational reliability, particularly under challenging conditions such as more stringent working-hour constraints, higher fixed costs, and varying network configurations. This robust performance underscores the model's potential as a valuable decision-support resource that helps planners navigate complex trade-offs between efficiency, reliability, and environmental considerations.

Several key insights emerged from our analyses. First, increasing the number of recycling facilities and appropriately tuning the robustness level can deliver more resilient solutions with minimal compromises in efficiency. Second, understanding the Price of Robustness enables decision-makers to balance operational cost increases against significant gains in reliability. Third, adjusting operating time limits, truck costs, and chance-constraint parameters provides a strategic toolkit for tailoring solutions to evolving regulatory, economic, and sustainability targets in urban waste management.

Despite these advances, there remain opportunities to strengthen and extend our work. Future research could incorporate more nuanced demand patterns, integrate broader sustainability metrics, or explore advanced data-driven methods for refining ambiguity sets. Additionally, addressing further operational complexities—such as dynamic location decisions, more granular driver workforce regulations, or mobile facilities—would enhance the model's applicability. By tackling these challenges, subsequent studies can build upon the robust foundation laid here, ultimately contributing to more sustainable, adaptable, and resilient waste management solutions in increasingly complex urban environments.

Chapter 6

Discussion and Implications

This research provides a comprehensive examination of circular construction challenges by integrating system dynamics, evolutionary game theory, and distributionally robust optimization. In doing so, it explicitly addresses the major problems outlined earlier: excessive resource consumption and waste generation in construction, the difficulty of aligning stakeholder behavior with sustainability goals, and inefficiencies in waste logistics. By uniting economic, policy, and operational perspectives, the study offers critical insights into how circular economy principles can be effectively implemented in the construction sector. The findings highlight key dynamics that influence the transition from traditional linear practices to circular ones, with broad implications for both global sustainability efforts and specific contexts such as urban Australia. This chapter discusses how these findings provide novel solutions to the identified problems, outlines the theoretical and practical contributions of the work, and demonstrates its real-world impact for policymakers, industry practitioners, and urban planners.

6.1 Addressing Key Challenges in Circular Construction

One major challenge in moving toward a circular construction model is aligning economic incentives to promote recycling and reuse. A significant insight from this study is the nonlinear relationship identified between waste disposal costs and recycling adoption. Traditional reasoning might suggest that gradually increasing landfill fees will linearly improve recycling rates. However, our system dynamics modeling revealed that even modest increases in landfill levies can trigger disproportionately large shifts in material flows. In other words, there appear to be tipping points where a small cost change causes a dramatic rise in recycling behavior. This nonlinear dynamic is a novel finding that suggests well-calibrated financial incentives could be far more effective than expected in accelerating circular practices. For example, strategically raising landfill disposal fees while subsidizing recycled aggregate prices may rapidly shift economic preferences in favor of recycling. At the same time, such strategies must be managed carefully to avoid unintended consequences. If higher landfill costs greatly increase the transportation of waste to distant recycling facilities, the added logistics burden could offset some environmental benefits. Thus, policymakers should seek an optimal balance that encourages recycling without introducing prohibitive logistic costs.

Another fundamental issue for circular construction is the interdependence of stakeholder decisions and policy measures. Sustainability policies do not operate in a vacuum; their success depends on how governments, construction firms, waste contractors, and consumers co-evolve their behaviors in response to these interventions. Our evolutionary game theory analysis demonstrates that dynamic, multi-faceted policy combinations tend to outperform any single policy measure in changing stakeholder behavior. For instance, while a penalty like a landfill tax or fine on unsustainable practices can induce immediate changes (e.g. discouraging illegal dumping or excessive waste), long-term adoption of circular practices is more robust when complementary incentives are also in place. Combinations of “carrot and stick” measures — such as moderate green taxation coupled with subsidies for using recycled materials, and public awareness campaigns highlighting the benefits of recycling — create a more supportive environment for voluntary participation in circular economy initiatives. The modeling showed that developers and contractors are more likely to invest in recycling technologies or use recycled concrete if they not only face higher costs for wastefulness but also receive tangible benefits (like tax credits or recognition) for sustainable practices. This insight addresses the earlier problem of fragmented stakeholder efforts by highlighting how coordinated policy packages can align diverse actors toward common sustainability goals. In short, a synergistic approach to policy design, rather than isolated interventions, is key to shifting industry norms and consumer attitudes in favor of circular construction.

A further challenge hampering circular construction is the logistical and operational complexity of closing material loops. The viability of recycling and reuse is greatly influenced by practical factors in the supply chain: the locations of recycling facilities, transportation distances, scheduling of waste collection, and overall infrastructure efficiency. Our results underscore that even if economic and regulatory incentives are strong, inadequate logistics can bottleneck progress. For example, in scenarios with high landfill fees intended to encourage recycling, excessive transportation costs or inefficient routing can erode the financial advantage of recycling, especially in geographically dispersed regions. The distributionally robust optimization of waste collection in this study highlights the importance of optimizing logistics networks to support circularity. By improving route efficiency for construction and demolition waste collection (for instance, using real-time route optimization algorithms) and by establishing decentralized waste processing hubs closer to major demolition sites, the cost and time penalties associated with recycling can be significantly reduced. These operational enhancements ensure that environmental gains from recycling are not lost to inefficiencies in moving materials. This finding directly tackles the practical problem of waste management inefficiency identified earlier, indicating that logistics optimization and circular economy policies must go hand-in-hand. Future policy frameworks could combine financial incentives with investments in smart logistics – for example, providing grants for companies to adopt route optimization technology or to build local recycling facilities – so that the economic, environmental, and operational aspects of circular construction are advanced in unison.

The relevance of these findings is clearly illustrated in the context of Australian construction waste management, which was a focal setting for this research. In Australia, the construction sector generates approximately 40% of the nation's total solid waste [Australian Bureau of Statistics, 2024]. Progressive policies such as landfill levies and sustainability certification programs have already raised recycling rates in certain states. Nevertheless, our analysis indicates that geographical factors and infrastructure gaps pose persistent barriers to a truly circular system. The vast distances between urban centers and centralized recycling plants create inefficiencies: long haul distances increase fuel use and costs, undermining the competitiveness of recycled aggregates against cheaper virgin materials. These logistical challenges help explain why even well-intentioned policies sometimes fall short of their full impact in practice. Addressing this issue requires an integrated approach that pairs policy incentives with infrastructure development. For example, enhancing local recycling capacity by investing in regional processing facilities would shorten transport distances, directly lowering the cost of recycling concrete and other materials. Likewise, promoting modular construction and design for disassembly can facilitate easier reuse of components, reducing the need to transport heavy materials long distances for processing. By improving the physical and technological infrastructure supporting recycling, Australia (and other regions facing similar spatial challenges) can amplify the effectiveness of circular economy policies. This study's findings support such strategic integration of regulatory support with on-the-ground infrastructure upgrades to overcome the twin hurdles of distance and scale in circular construction.

Concrete recycling, examined in depth in this research, serves as a microcosm of both the opportunities and hurdles inherent in the circular construction transition. Technically, recycled concrete aggregates have substantial potential to replace virgin aggregates in many applications, which could drastically reduce the demand for new raw materials. Economically, reusing concrete waste can save on material costs and landfill fees. However, our findings acknowledge that widespread adoption of recycled concrete is still hindered by several practical issues: regulatory uncertainty (inconsistent or overly strict regulations on recycled material use), market hesitancy (construction stakeholders may be wary of using recycled products due to perceived quality or reliability concerns), and inconsistent quality standards (a lack of uniform standards for recycled aggregate can lead to variable performance outcomes). These challenges were identified as key problems in earlier chapters, and our study offers insight into how they might be overcome. One promising avenue is technological innovation. Advances in processing are yielding higher-grade recycled concrete that meets stringent strength and durability requirements. Additionally, digital tracking systems such as building material passports can record the provenance and properties of materials, thereby increasing confidence in recycled components by ensuring quality assurance and traceability. If such innovations are coupled with supportive policies — for instance, government procurement mandates that require a minimum percentage of recycled content in public construction projects — they could significantly boost market acceptance of recycled concrete. The implication is that through a combination of innovation, information transparency, and policy leadership, the construction industry can break the current barriers and rapidly accelerate the use of recycled materials. In solving the concrete recycling puzzle, we not only divert vast amounts of waste from landfills but also reduce demand for virgin aggregate mining, directly addressing resource depletion concerns.

6.2 Theoretical Contributions of an Integrated Approach

Beyond these domain-specific findings, this dissertation makes several important theoretical contributions to the scholarly discourse on sustainable systems and operational research. A primary contribution is the development of an integrated modeling framework that bridges system-level dynamics, stakeholder behavior, and operational decision-making. By combining System Dynamics, Evolutionary Game Theory, and Distributionally Robust Optimization into one cohesive study, we have demonstrated a novel interdisciplinary approach to investigating circular economy problems. Each of these methodologies has traditionally been applied in isolation within sustainability research: system dynamics to capture macro-level feedback loops, game theory to analyze strategic interactions, and optimization to improve logistics and operations. In this work, however, we show the value of linking these approaches. The integrated framework provides a more holistic theoretical lens, allowing us to capture complex phenomena (such as policy feedback loops and behavioral adaptation over time) that no single method could fully address on its own.

This multi-method approach advances academic understanding by highlighting how economic, behavioral, and operational subsystems interact in the context of circular construction. For example, the finding of nonlinear policy impacts on recycling rates contributes to theoretical knowledge of feedback effects in economic systems – illustrating a tipping-point behavior that enriches classic environmental economics models. Similarly, our application of evolutionary game theory in a policy context extends theoretical models of stakeholder co-evolution, offering a quantitative depiction of how mixed incentives can lead to stable equilibrium outcomes that favor sustainability. In the operations research realm, the formulation of a distributionally robust optimization for waste collection under uncertainty is a theoretical contribution in itself, as it adapts advanced optimization techniques to the domain of construction logistics and demonstrates their efficacy in handling ambiguity in waste generation and travel times. This cross-pollination of methods yields insights that are more than the sum of their parts: it suggests, for instance, new theoretical conjectures about how policy-driven behavior change can alter system parameters in an optimization model, or how operational constraints can feed back into strategic stakeholder decisions.

Moreover, the research contributes to the circular economy literature by providing a quantitative, model-based exploration of circular construction transitions. Much of the existing circular economy theory is conceptual or qualitative, emphasizing principles and broad frameworks. Our work adds rigor by underpinning those concepts with formal models and simulations, thereby helping to validate and refine theoretical principles using data-driven analysis. The integrated model can serve as a blueprint for scholars exploring other complex sustainability transitions (e.g., in waste management or renewable energy deployment), illustrating how multiple theoretical lenses can be combined to capture reality more completely. In essence, this study's approach pushes academic discourse towards embracing interdisciplinary methods, reinforcing the idea that solving entrenched sustainability challenges often requires blending insights from systems science, economics, and engineering. By doing so, it opens up new avenues for theoretical research — for instance, future studies might build on our framework to develop unified theories that link policy, behavior, and technology adoption dynamics in circular economy contexts. Such an enriched theoretical perspective is a key contribution of this work, enhancing our collective understanding of how to steer industries like construction towards sustainability.

6.3 Practical Implications and Real-World Impact

In addition to theoretical advances, this research delivers practical contributions with immediate relevance for policymakers, industry practitioners, and urban planners aiming to implement circular construction and improve waste management systems. The insights from the models translate into concrete strategies that these stakeholders can apply to optimize operations, encourage sustainable practices, and reduce resource depletion in the real world. Key applications and recommendations include:

Policymakers and Regulators: Government authorities can draw on these findings to design more effective sustainability policies and regulations. Rather than relying on a single policy lever, policymakers should implement multi-pronged policy packages that combine economic incentives with regulatory measures and education. For example, a city council might increase landfill levies modestly while simultaneously offering subsidies or tax credits for using recycled construction materials, leveraging the identified nonlinear effects to rapidly shift economic behavior. At the same time, complementary measures such as public awareness campaigns about the benefits of recycled materials can improve acceptance and compliance. Regulators are also advised to introduce clear quality standards and certification for recycled materials (like recycled aggregate concrete) to reduce uncertainty in the marketplace. Additionally, adaptive policy mechanisms are recommended: using real-time data on waste generation and recycling rates, governments could adjust fees or incentives dynamically (for instance, raising fees if recycling stagnates, or increasing subsidies if recycled material supply outpaces demand) to keep the system on track toward circularity. By enacting coherent and flexible policy frameworks in this way, policymakers can create an environment in which sustainable construction practices flourish organically.

Industry Practitioners (Construction and Waste Management Firms): For companies in the construction supply chain — from builders and developers to demolition contractors and waste service providers — the research highlights strategies to improve both sustainability and profitability. Firms should embrace innovative technologies and materials that enable circular construction. In practice, this means increasing the use of high-quality recycled materials (such as certified recycled concrete aggregates) in new projects and investing in technologies like material tracking systems (e.g. digital material passports) to monitor and ensure the quality of reused components. Construction companies can proactively comply with or even exceed any recycled content requirements in projects, positioning themselves as leaders in sustainability and gaining early experience with circular techniques. Waste management and logistics firms, on the other hand, can implement advanced route optimization software and fleet management systems to enhance collection efficiency as recommended by our optimization model. By reducing empty runs and optimizing schedules for skip bin pickups and deliveries, firms can lower operational costs and emissions, making recycling services more economically attractive. Collaboration across the industry is also crucial: stakeholders could form partnerships where demolition waste from one project becomes input for another, facilitated by marketplaces or exchanges for secondary materials. The findings suggest that companies adopting these practices will not only reduce their environmental footprint but also stand to benefit from lower waste disposal fees and new business opportunities in the recycling market, thereby aligning sustainability with commercial success.

Urban Planners and Infrastructure Developers: Urban planners and municipal authorities play a key role in creating the physical and logistical environment needed for a circular economy. Based on this research, planners should integrate waste management infrastructure planning into urban development. This could involve zoning decisions that allocate land for local recycling facilities or material recovery centers strategically near demolition and construction hotspots to minimize transport distances. Investing in a network of such decentralized facilities aligns with our finding that proximity is critical to economic viability for recycling. Planners are also encouraged to promote design-for-reuse principles in building codes and development guidelines – for example, favoring modular construction, which allows building components to be easily dismantled and reused or recycled. By influencing the design phase, planners can help ensure that new buildings are essentially "material banks" for the future, thereby reducing waste generation at the source. In terms of transportation planning, incorporating logistics considerations for construction waste (such as designated routes or off-peak haulage incentives to reduce congestion and emissions) can improve the overall sustainability of construction logistics. Urban authorities might also use the simulation models from this study as decision-support tools: for instance, to test how different policy or infrastructure changes could impact city-wide waste flows and recycling rates over time. The practical implication is that urban planning must go hand-in-hand with environmental policy – cities that proactively develop the required infrastructure and embed circular principles into their planning processes will be better positioned to reap the benefits of sustainable construction.

By applying these strategies, real-world stakeholders can significantly improve waste management outcomes and advance sustainable construction logistics. Policymakers implementing combined and adaptive policies will see more waste diverted from landfills and higher recycling participation. Industry practitioners optimizing their operations and embracing recycled materials will reduce costs and resource consumption, all while meeting evolving regulatory standards and public expectations. Urban planners who build circular economy considerations into the fabric of city design will facilitate shorter supply chains and more efficient resource loops. Collectively, these actions help optimize waste management systems, reducing inefficiencies and costs in collection and processing. They also improve the sustainability of construction logistics by cutting down unnecessary transport and promoting reuse of materials (thereby lowering carbon emissions and traffic impacts). Most importantly, widespread adoption of these recommendations contributes to reducing resource depletion: by maximizing the reuse of construction materials like concrete, we decrease the demand for extracting and producing virgin materials such as cement, gravel, and sand. Over time, this means preserving natural resources and minimizing the environmental damage associated with raw material production. In sum, the insights from this research provide a roadmap for translating circular economy theory into practice, enabling tangible progress toward a more sustainable and resource-efficient built environment.

6.4 Limitations and Future Research

While this study offers robust findings and recommendations, it is important to acknowledge its limitations and the opportunities they create for future research. First, like any modeling endeavor, our simulations and optimization results are subject to uncertainties in their input data and assumptions. Some parameters—such as precise logistics costs, the responsiveness of stakeholders to policy changes, or the rate of technology adoption—were based on the best available data and reasonable estimates, but real-world values can vary. These data constraints introduce some uncertainty into the results. For instance, if actual transportation costs differ significantly from those assumed, the exact tipping point at which recycling becomes profitable would shift. Similarly, stakeholder behavior in reality may not exactly follow the patterns predicted by evolutionary game theory, especially given diverse human factors and external influences. These considerations mean that, although the direction of our insights is expected to hold, the quantitative magnitudes and specific break-even points should be interpreted with caution. Another limitation is the scope of scenarios examined. The models were calibrated for the Sydney metropolitan context and focused on particular policy and operational levers; as such, the findings may need adaptation before applying to different regions or scales (e.g., rural areas or countries with different regulatory regimes).

Future research should aim to refine and extend the modeling approach to address these limitations. One important avenue is to incorporate more granular and real-time data into the analyses. For example, obtaining detailed transportation data (fuel costs, distances, traffic patterns) and dynamic waste generation data would allow for more precise optimization of logistics and better validation of the system dynamics model. Likewise, conducting surveys or behavioral experiments with construction industry stakeholders could improve the calibration of the game-theoretic model by grounding it in observed decision-making patterns. Expanding the geographical and temporal scope of the study would also be valuable: analyzing circular construction initiatives in other cities or countries, or over longer planning horizons, could test the generalizability of the findings and adapt the recommendations to various contexts. Moreover, future studies might integrate additional operational complexities that were beyond the scope of this dissertation. For instance, incorporating decisions about the location of recycling facilities (not just their presence) into the optimization model, or considering workforce and equipment constraints in waste collection, would make the logistical analysis even more reflective of real-world conditions. There is also potential to explore the interaction between different waste streams – the current model focuses on concrete and construction waste, but integrating it with models of other recyclable materials (wood, metal, etc.) could lead to a comprehensive strategy for all construction and demolition waste.

Another promising direction for future research is the use of emerging digital technologies to enhance both policymaking and operations in the circular economy. The study hints at possibilities like blockchain-enabled waste tracking and machine learning-based forecasting. Building on this, researchers could develop adaptive policy frameworks that automatically adjust incentives or regulations based on live data feeds of material flows (for example, using smart contracts on a blockchain to modify a recycling subsidy when certain waste reduction targets are met). Similarly, machine learning models could improve the prediction of waste supply and demand, enabling more responsive scheduling and scaling of recycling operations. Integrating artificial intelligence into the logistics optimization—such as algorithms that learn and update routes in real time in response to traffic or waste volume fluctuations—could further increase the efficiency gains identified in our robust optimization model. Pursuing these advanced tools would require interdisciplinary collaboration, combining insights from data science with engineering and economics, but could greatly enhance the responsiveness and resilience of circular construction systems. Ultimately, by addressing the data gaps and extending the models in these ways, future research can build upon the foundation laid by this dissertation. Such efforts will deepen our understanding of circular economy transitions and support the development of policies and technologies that are even more effective in steering the construction industry toward sustainability.

Overall, this study contributes significantly to the pursuit of a truly circular built environment by providing both a broad vision and specific guidance for achieving sustainable construction practices. Through the integration of economic, behavioral, and operational analyses, it demonstrates how leveraging feedback effects, stakeholder cooperation, and optimized logistics can overcome the entrenched linear habits of the construction sector.

The findings offer actionable insights for decision-makers at multiple levels: policymakers gain evidence-based strategies for crafting effective interventions, industry leaders receive a blueprint for aligning profitability with sustainability, and researchers are given a validated framework for further investigation. In bridging gaps between theory and practice, the research enhances academic discourse with an interdisciplinary methodology and at the same time charts practical pathways to implementation. Realizing the full potential of circular construction will require concerted, multi-faceted efforts. The evidence presented here suggests that no single policy, technology, or business model will suffice; instead, success lies in the synergy of approaches – combining economic incentives with strict regulations and educational initiatives, pairing technological innovation with infrastructure investment, and encouraging collaboration among all stakeholders in the construction ecosystem. By making the case for such an integrated approach and illustrating its benefits, this dissertation lays important groundwork for future progress. The implications extend beyond the case of Sydney or the construction sector alone, offering lessons applicable to many regions and industries striving to balance development with sustainability. In conclusion, the research underscores that transitioning to a circular economy in construction is both achievable and urgently necessary. With informed policymaking, proactive industry adaptation, and strategic planning, the cycle of resource use can be closed. This would mark a substantial step toward sustainable urban development—reducing waste, preserving natural resources, and promoting economic efficiency for generations to come.

Chapter 7

Conclusion

The construction industry consumes approximately 40% of global raw materials and generates one-third of worldwide waste, making its transformation toward circular practices essential for achieving global sustainability targets. As urban populations continue to grow and resource constraints intensify, the transition from linear "take-make-dispose" models to regenerative construction systems represents both an environmental imperative and an economic opportunity. This dissertation has addressed this challenge through an integrated analytical framework that bridges economic dynamics, stakeholder behavior, and operational optimization to provide practical pathways for implementing circular construction principles.

This research makes three distinct methodological and empirical contributions to circular construction knowledge. The System Dynamics analysis of concrete recycling revealed critical economic thresholds where modest policy interventions trigger substantial behavioral shifts. Specifically, reducing recycling logistics costs below $485 per ton creates a tipping point where recycling rates accelerate dramatically, while a 10% increase in landfill fees can divert over 95% of concrete waste from landfills to recycling facilities. These findings quantify the nonlinear relationships between economic incentives and material flow patterns, providing policymakers with precise targets for intervention design.

The evolutionary game theory framework represents the first integration of game-theoretic analysis with system dynamics modeling for stakeholder behavior in construction sustainability. This approach demonstrated that dynamic policy combinations—incorporating graduated taxation, public awareness campaigns, and green financing—achieve system-wide green construction adoption 50% faster than static policy approaches. The analysis revealed that stakeholder interactions exhibit path-dependent evolution, where early adoption by one group catalyzes broader industry transformation, emphasizing the critical importance of policy sequencing and timing.

The distributionally robust optimization model for skip logistics addresses a previously unstudied problem in construction waste management under uncertainty. This framework reduces service constraint violations by 95% compared to deterministic approaches, with only a 2% increase in operational costs. The analysis demonstrated that strategic facility placement and robust scheduling can reduce transportation barriers to recycling by up to 30%, directly enhancing the economic viability of circular material flows.

This dissertation pioneers the integration of three complementary analytical approaches System Dynamics, evolutionary game theory, and distributionally robust optimization—to address the multi-dimensional challenges of circular construction implementation. This methodological integration enables comprehensive analysis of economic incentives, stakeholder interactions, and operational constraints within a unified framework. The approach demonstrates how complex sustainability challenges require interdisciplinary solutions that individual methods cannot adequately capture. The research establishes empirical validation protocols for each methodology, including stakeholder consultation for model calibration, sensitivity analysis across parameter ranges, and out-of-sample testing for robustness verification.

Based on the integrated findings, this research provides a phased implementation roadmap for circular construction adoption. The foundation building phase focuses on establishing baseline metrics, implementing route optimization systems achieving

5-10% logistics cost reductions, and initiating stakeholder consultation processes. The policy introduction phase involves graduated landfill levies starting at $25-50 per ton, public awareness campaigns targeting 15-20% of sustainability budgets, and green financing partnerships offering 5-10% interest rate reductions. The system scaling phase consolidates gains by achieving target cost differentials ensuring 85-90% recycling rates, scaling successful facility networks, and establishing adaptive management systems for long-term optimization.

The research provides targeted guidance for different practitioner communities. Waste logistics operators should prioritize service reliability over marginal cost efficiency, implementing distributed facility networks and maintaining 10-15% operational time buffers to accommodate uncertainty. City planners should position recycling facilities within 15-20 kilometers of major construction zones and implement graduated policy increases rather than shock interventions. Construction industry stakeholders should pursue early green adoption strategies, recognizing that first-movers benefit from competitive advantages as market conditions evolve toward sustainability requirements. Financial institutions and policymakers should coordinate green financing programs with regulatory frameworks, creating synergistic effects that accelerate adoption while maintaining market stability.

While this research provides valuable insights, several limitations warrant acknowledgment. The System Dynamics model is calibrated specifically for Sydney's urban context and may require substantial adjustment for cities with different geographic, regulatory, or economic characteristics. The game-theoretic analysis assumes rational stakeholder behavior, which may not fully capture real-world decision-making complexity influenced by organizational culture, risk aversion, or information asymmetries. The skip optimization model addresses travel time uncertainty but does not account for demand volatility, facility capacity constraints, or equipment failure scenarios.

Future research should extend this framework in several specific directions. Real-time sensor integration for dynamic material flow tracking could enhance model responsiveness and accuracy. Multi-city comparative studies would test model transferability and identify context-specific adaptation requirements. Machine learning integration could refine stakeholder behavior predictions and improve policy effectiveness forecasting. Expanding the analytical scope to include steel, timber, and other construction materials would provide comprehensive circular economy frameworks beyond the concrete focus of this research.

This research demonstrates that circular construction represents not merely an environmental aspiration but an economically viable and operationally feasible transformation pathway. The quantified thresholds, behavioral insights, and optimization strategies provide evidence that well-designed interventions can overcome the economic and logistical barriers that have historically limited circular practice adoption. The findings have particular relevance for rapidly urbanizing regions facing intense resource pressure and waste management challenges, with the methodological framework adaptable to diverse contexts as a blueprint for analyzing sustainability transitions in other cities, industries, and resource systems.

As global climate commitments intensify and resource scarcity accelerates, implementing circular construction principles becomes increasingly critical for achieving sustainability targets. This research provides both the analytical tools and practical guidance necessary to transform construction industry practices, contributing to broader efforts to build resilient, resource-efficient urban systems. The transition toward circular construction requires coordinated action across multiple stakeholder groups, supported by evidence-based policy design and optimized operational strategies. Through this integrated approach, the construction industry can evolve from a major contributor to environmental degradation into a driver of sustainable urban development, demonstrating that economic prosperity and environmental stewardship are not only compatible but mutually reinforcing objectives.

Appendix A

A1 Proof of Proposition 5.1

Proof. Because the ambiguity set $\mathcal{F}_1$ is composed by marginal information for each dimension of the vector $\tilde{\boldsymbol{\tau}}$, the following equality holds:

$$\begin{aligned}
&\sup_{\mathbb{P}\in\mathcal{F}_1} \mathbb{P}\text{-VaR}_{1-\epsilon}[f_{m,t}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z},\tilde{\boldsymbol{\tau}})] \leq D \iff \\
&\sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{I}} \sup_{\mathbb{P}\in\mathcal{F}_1} \mathbb{P}\text{-VaR}_{1-\epsilon}[\tilde{\tau}_{i,v} z_{v,m,t}(x^1_{i,m,t} + x^2_{i,m,t})] \\
&+ \sum_{v\in\mathcal{V}}\sum_{i,j\in\mathcal{I}} \sup_{\mathbb{P}\in\mathcal{F}_1} \mathbb{P}\text{-VaR}_{1-\epsilon}[\tilde{\tau}_{i,j,v} y_{i,j,m,t}]
\end{aligned}$$

Further, by Proposition 2 of Ghosal and Wiesemann [2020], we know that:

$$\begin{aligned}
\sup_{\mathbb{P}\in\mathcal{F}_1} \mathbb{P}\text{-VaR}_{1-\epsilon}[\tilde{\tau}_{i,v}] &= \mu_{i,v} + \min\left(\overline{\tau}_{i,v} - \mu_{i,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,v} - \underline{\tau}_{i,v}), \frac{1}{2\epsilon}\sigma_{i,v}\right), \\
\sup_{\mathbb{P}\in\mathcal{F}_1} \mathbb{P}\text{-VaR}_{1-\epsilon}[\tilde{\tau}_{i,j,v}] &= \mu_{i,v} + \min\left(\overline{\tau}_{i,j,v} - \mu_{i,j,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,j,v} - \underline{\tau}_{i,j,v}), \frac{1}{2\epsilon}\sigma_{i,j,v}\right)
\end{aligned}$$

Let

$$\begin{aligned}
\tau^*_{i,j} &= \mu_{i,v} + \min\left(\overline{\tau}_{i,v} - \mu_{i,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,v} - \underline{\tau}_{i,v}), \frac{1}{2\epsilon}\sigma_{i,v}\right), \\
\tau^*_{i,j,v} &= \mu_{i,v} + \min\left(\overline{\tau}_{i,j,v} - \mu_{i,j,v}, \frac{1-\epsilon}{\epsilon}(\mu_{i,j,v} - \underline{\tau}_{i,j,v}), \frac{1}{2\epsilon}\sigma_{i,j,v}\right)
\end{aligned}$$

The proof is now complete. □

A2 Skip demand by council area

Table A.1. Skip demand by council area

Council Name	No.	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Total
Blacktown City Council	1	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	9
Fairfield City Council	2	no	no	yes	no	yes	yes	yes	no	no	no	4
Cumberland Council	3	yes	yes	no	yes	no	no	yes	no	no	no	4
Penrith City Council	4	yes	no	no	yes	no	yes	no	no	yes	no	4
Parramatta City Council	5	no	yes	yes	yes	no	no	yes	yes	no	no	5
The Hills Shire Council	6	yes	no	no	no	yes	no	yes	no	no	yes	4
Hornsby Shire Council	7	no	no	yes	no	no	yes	no	no	yes	no	3
Canada Bay Council	8	no	yes	no	no	no	no	no	yes	no	no	2
Mosman Municipal Council	9	no	no	no	no	no	no	yes	no	no	no	1
Strathfield Council	10	no	no	yes	no	no	no	no	no	no	no	1
Ryde City Council	11	no	no	no	no	yes	no	no	no	yes	no	2
Inner West Council	12	no	no	no	yes	no	yes	no	yes	no	no	3
Lane Cove Council	13	no	no	no	no	no	no	yes	no	no	no	1
Bayside Council	14	yes	no	no	yes	no	no	no	yes	no	no	3
Woollahra Municipal Council	15	no	yes	no	no	no	no	no	no	no	no	1
Willoughby City Council	16	no	no	no	no	no	yes	no	no	no	no	1
Ku-ring-gai Council	17	no	no	no	yes	yes	no	no	no	no	no	2
Waverley Council	18	no	no	no	no	no	no	no	no	yes	no	1
Randwick City Council	19	yes	no	yes	no	no	no	yes	no	no	no	3
Burwood Council	20	no	no	no	no	no	no	no	yes	no	no	1
City of Sydney	21	yes	yes	no	yes	no	no	no	no	yes	no	4
North Sydney Council	22	no	no	no	no	no	no	no	yes	no	no	1
Hunter’s Hill Council	23	no	no	no	no	no	no	yes	no	no	no	1
Northern Beaches Council	24	no	yes	no	no	yes	no	no	yes	no	no	3
Camden Council	25	no	no	yes	no	no	no	yes	no	no	no	2
Georges River Council	26	no	yes	no	yes	no	yes	no	no	no	no	3
Sutherland Shire Council	27	yes	no	yes	no	no	no	yes	yes	no	no	4
Liverpool City Council	28	no	yes	no	yes	yes	no	no	no	yes	no	4
Campbelltown City Council	29	no	no	no	no	no	yes	no	yes	no	no	2
Canterbury-Bankstown Council	30	no	no	yes	yes	no	no	no	no	yes	no	3
Total	-	7	8	8	10	6	8	11	10	8	6	82

A3 Detailed daily route operations under base DRO-chance model

This appendix provides a comprehensive day-by-day breakdown of skip task assignment operations across the Sydney Metropolitan Area under base DRO-Chance model.

Day 2

Truck 1 operations

Starting Location: Eastern Creek Depot

(1) Deliver empty skip to Blacktown City Council
(2) Return to Eastern Creek Depot
(3) Deliver empty skip to Cumberland Council
(4) Return to Eastern Creek Depot
(5) Deliver empty skip to Parramatta City Council
(6) Return to Eastern Creek Depot
(7) Deliver empty skip to Georges River Council
(8) Return to Eastern Creek Depot
(9) Deliver empty skip to Liverpool City Council
(10) Return to Eastern Creek Depot

Truck 2 operations

Starting Location: Belrose Depot

(1) Deliver empty skip to Canada Bay Council
(2) Return to Belrose Depot

(3) Deliver empty skip to Woollahra Municipal Council
(4) Return to Belrose Depot
(5) Deliver empty skip to City of Sydney
(6) Return to Belrose Depot
(7) Deliver empty skip to Northern Beaches Council
(8) Return to Belrose Depot

Day 5

Truck 1 operations

Starting Location: Eastern Creek Depot

(1) Deliver empty skip to Blacktown City Council
(2) Pick up full skip from Blacktown City Council
(3) Return to Eastern Creek Depot
(4) Deliver empty skip to Fairfield City Council
(5) Pick up full skip from Georges River Council
(6) Return to Eastern Creek Depot
(7) Deliver empty skip to The Hills Shire Council
(8) Pick up full skip from Cumberland Council
(9) Return to Eastern Creek Depot
(10) Deliver empty skip to Liverpool City Council
(11) Pick up full skip from Liverpool City Council
(12) Return to Eastern Creek Depot

Truck 2 operations

Starting Location: Belrose Depot

(1) Deliver empty skip to Ryde City Council
(2) Pick up full skip from Canada Bay Council
(3) Return to Belrose Depot
(4) Pick up full skip from Woollahra Municipal Council
(5) Return to Belrose Depot
(6) Deliver empty skip to Ku-ring-gai Council
(7) Pick up full skip from Parramatta City Council
(8) Return to Belrose Depot
(9) Pick up full skip from City of Sydney
(10) Return to Belrose Depot
(11) Deliver empty skip to Northern Beaches Council
(12) Pick up full skip from Northern Beaches Council
(13) Return to Belrose Depot

Day 11

Truck 1 operations

Starting Location: Lucas Heights Depot

(1) Pick up full skip from Parramatta City Council
(2) Return to Lucas Heights Depot
(3) Pick up full skip from Bayside Council
(4) Return to Lucas Heights Depot
(5) Pick up full skip from Burwood Council
(6) Return to Lucas Heights Depot
(7) Pick up full skip from Sutherland Shire Council
(8) Return to Lucas Heights Depot

(9) Pick up full skip from Campbelltown City Council
(10) Return to Lucas Heights Depot

Truck 2 operations

Starting Location: Belrose Depot

(1) Pick up full skip from Blacktown City Council
(2) Return to Belrose Depot
(3) Pick up full skip from Canada Bay Council
(4) Return to Belrose Depot
(5) Pick up full skip from Inner West Council
(6) Return to Belrose Depot
(7) Pick up full skip from North Sydney Council
(8) Return to Belrose Depot
(9) Pick up full skip from Northern Beaches Council
(10) Return to Belrose Depot

Operational notes

- Each return to depot involves dropping off full skips and/or picking up empty skips for next delivery
- Routes are optimized to service specific geographic regions from each depot
- Operations transition from predominantly empty skip deliveries (Days 1-3) to mixed operations (Days 4-9) to predominantly full skip collections (Days 10-13)
- Four main recycling facilities service the region:
  - Lucas Heights Depot - Services southern Sydney
  - Eastern Creek Depot - Services western Sydney
  - Belrose Depot - Services northern Sydney

- Jacks Gully Depot - Services southwestern Sydney

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