

Multi-Objective Optimization of Sustainable Purchase and Procurement Under Circular Economy Principles

Abstract: This report presents a comprehensive study on optimizing sustainable purchasing and procurement by applying multi-objective optimization techniques under circular economy principles.

70 min read • 26 sections • LISRC R&D practice



LISRC Research & Development

The applied-research practice of London International Studies & Research Centre

Research and Development Department · Published: February 2025

Abstract: This report presents a comprehensive study on optimizing sustainable purchasing and procurement by applying multi-objective optimization techniques under circular economy principles. Sustainable procurement aims to achieve triple bottom line outcomes – economic, environmental, and social benefits – but these objectives often conflict. We integrate circular economy principles (waste reduction, resource reuse) with advanced optimization methods to support decision-makers in balancing cost efficiency with environmental stewardship and social responsibility. A mathematical framework is developed, and solution approaches including Linear Programming (LP), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) are applied to model procurement decisions with multiple objectives. The report provides detailed formulations and pseudocode for each method, and evaluates their performance on case studies in public sector procurement and industry supply chains. Results demonstrate that multi-objective optimization yields a set of Pareto-optimal procurement

strategies, enabling significant cost savings alongside reductions in waste and carbon footprint. We discuss the comparative advantages of exact vs. heuristic methods, the challenges in practical implementation, and the role of such optimized procurement in advancing circular economy goals. Finally, policy implications and future research directions are outlined to guide the adoption of sustainable procurement optimization in practice.

01 Introduction

In recent years, organizations worldwide have increasingly recognized the need to integrate sustainability into purchasing and procurement decisions. Traditional procurement practices focused primarily on cost and quality; however, modern sustainable procurement expands this focus to include environmental stewardship and social responsibility. This shift is driven by global concerns such as resource depletion, climate change, and social equity, and is encapsulated in the concept of the circular economy. A circular economy is an economic system aimed at eliminating waste and promoting the continual use of resources, in contrast to the linear “take-make-dispose” model of production and consumption. It is based on three core principles – designing out waste and pollution, keeping products and materials in use, and regenerating natural systems. By reusing, refurbishing, and recycling materials, the circular economy seeks to extend product lifecycles and reduce the need for virgin resources.

Sustainable procurement serves as a critical lever for advancing circular economy objectives. By carefully selecting what goods and services to purchase and from whom, governments and companies can influence supply chains to become more sustainable and circular. According to the United Nations Environment Programme, sustainable procurement can accelerate the transition to a circular economy and shift consumption and production patterns towards sustainability. Indeed, many public institutions are beginning to incorporate circular criteria into procurement policies – for example, requiring a percentage of recycled content or end-of-life take-back provisions in contracts. The 2017 Global Review of Sustainable Public Procurement (SPP) highlights that SPP is becoming a widespread practice, with activities on the rise across all types of organizations. This trend reflects a growing acknowledgment that procurement decisions have far-reaching impacts on environmental outcomes (such as waste

generation and greenhouse gas emissions) and social outcomes (such as labor practices and community well-being).

However, integrating sustainability into procurement is inherently a multi-objective decision problem. Procurers must balance the economic objective of cost minimization with environmental objectives (e.g. minimizing carbon footprint, reducing waste) and often social objectives (e.g. supporting local businesses or fair labor). The triple bottom line framework introduced by Elkington posits that organizations should give equal weight to social, environmental, and financial performance. In practice, these objectives can conflict: for instance, products with lower environmental impact may come at a higher price, or prioritizing local suppliers (social benefit) might conflict with cost efficiency if local options are more expensive. Traditional single-objective approaches are ill-suited to address these trade-offs. Instead, what is required is an approach that can handle multiple objectives simultaneously, providing decision-makers with a set of optimal trade-off solutions.

Multi-objective optimization techniques offer a means to systematically tackle such trade-offs. Rather than producing a single "optimal" solution, multi-objective optimization yields a set of Pareto optimal solutions, each of which is non-dominated (i.e. no objective can be improved without worsening at least one other objective). This Pareto frontier allows procurement managers to understand the landscape of possible outcomes – for example, how much additional cost would be incurred to achieve a given level of emissions reduction – and then make informed decisions aligned with organizational priorities or policy goals. In the context of sustainable procurement under circular economy principles, multi-objective optimization can help answer questions like: What is the minimum achievable environmental impact for a given budget? Or conversely, what is the minimal cost increase required to significantly improve environmental and social performance?

This research is conducted under the aegis of the London International Studies and Research Center (London INTL), in collaboration with its Research and Development Department, to develop a framework for optimizing procurement practices with environmental, economic, and social considerations. We combine operations research methods and advanced evolutionary algorithms to address the sustainable procurement problem. In particular, we formulate a mathematical model of the procurement decision that captures circular economy considerations (such as reuse and recycling flows) and

multiple objectives. We then apply and compare three solution approaches: (1) traditional Linear Programming (LP) techniques (extended to handle multiple objectives via goal programming and weighted-sum methods), (2) a Genetic Algorithm (GA) tailored for multi-objective optimization, and (3) a Particle Swarm Optimization (PSO) approach for multi-objective search. The GA and PSO are metaheuristic techniques inspired by natural processes – GAs mimic biological evolution via selection, crossover, and mutation, while PSO is inspired by the social behavior of flocking birds or schooling fish. These population-based algorithms are well-suited to exploring large, complex solution spaces and approximating Pareto-optimal fronts for multiple objectives.

The remainder of this report is structured as follows. Section 2 reviews the relevant literature and background on sustainable procurement, circular economy principles, and multi-objective optimization applications in supply chain management. Section 3 outlines the methodology, including the conceptual framework and solution techniques, with pseudocode provided for the GA, PSO, and multi-objective LP approaches. Section 4 presents the mathematical models in detail, formulating the procurement optimization problem and describing how the objectives and constraints are modeled. Section 5 describes the implementation of these models and algorithms, including any assumptions, data requirements, and computational tools used. Section 6 provides several case studies – including a public sector procurement scenario and an industrial supply chain scenario – illustrating the application of the proposed approach and discussing results with real-world data. Section 7 compares the results across case studies and discusses key findings, including the performance of different optimization methods. Section 8 discusses the practical challenges of implementing sustainable procurement optimization and how these might be mitigated. Section 9 outlines future research directions and improvements, such as incorporating uncertainty and new technologies like blockchain and AI. Finally, Section 10 concludes the report, highlighting the contributions of this work and the importance of multi-objective optimization in achieving sustainable, circular procurement practices.

02 Literature Review

03 Sustainable Procurement and Circular Economy Principles

Sustainable procurement is broadly defined as the process of acquiring goods and services in a way that achieves value for money on a whole-life basis while benefitting society and the economy, and minimizing damage to the environment. It is an implementation of the concept of sustainability in the procurement function of organizations. Many governments and corporations have developed sustainable procurement policies that embed criteria such as environmental performance, social responsibility, and ethical considerations into procurement decisions. For instance, the World Bank and United Nations agencies now include sustainability criteria in bidding processes for projects, and the European Union has developed Green Public Procurement (GPP) guidelines to help public authorities purchase products with a lower environmental footprint.

The circular economy (CE) concept is central to environmental sustainability in procurement. In a circular economy, value retention and recovery processes like reuse, remanufacturing, and recycling are emphasized so that the end-of-life of one product becomes the feedstock for another, forming a closed-loop system. The Ellen MacArthur Foundation, a leading voice on circular economy, describes it as an economy based on designing out waste and pollution, keeping products and materials in use for as long as possible, and regenerating natural systems. Applying these principles to procurement means that purchasing decisions should favor products that are durable, repairable, recyclable, or made from recycled materials, and suppliers that offer take-back schemes or use renewable inputs. For example, a circular procurement approach in electronics might prioritize laptops that are refurbished or modular (for easy part replacement), and include contract terms for vendor take-back and recycling of old equipment.

By leveraging procurement in this way, organizations can drive circularity in supply chains. A report by the World Economic Forum found that companies implementing sustainable procurement can not only reduce their environmental impact but also realize financial benefits, such as a 5–20% increase in revenue and 9–16% reduction in supply chain costs on average. These figures illustrate the potential win-win of well-designed sustainable procurement strategies: reduced environmental footprint along with cost

savings, often through efficiency gains and waste reduction. Additionally, sustainable procurement can enhance brand value and reduce risk by ensuring more resilient supply chains and compliance with emerging regulations (e.g., on carbon emissions or waste).

There is a growing body of case studies demonstrating successful integration of circular economy principles into procurement. For instance, an Italian initiative on circular public procurement in construction found that requiring recycled materials and waste-minimization plans in public works contracts led to significant reductions in landfill waste without increasing costs (One Planet Network, 2020). Similarly, several cities in the Netherlands and Scandinavia have piloted circular procurement for furniture and textiles, achieving high rates of material reuse. These cases underscore that, with the right criteria and supplier engagement, circular procurement can be practical and beneficial. Nonetheless, they also highlight challenges, such as the need for reliable metrics to evaluate circularity and the importance of market availability of sustainable alternatives. This points to the need for decision-support tools (like optimization models) to help procurement officials quantitatively evaluate options under multiple criteria.

04 **Triple Bottom Line Objectives in Supply Chain Management**

The notion of pursuing multiple objectives in supply chain and operations management is not new. The triple bottom line (TBL) – often summarized as “People, Planet, Profit” – provides a foundational perspective that sustainability performance encompasses social (people) and environmental (planet) dimensions in addition to economic (profit). The term was popularized by John Elkington in the late 1990s to encourage businesses to broaden their focus beyond profit alone. In procurement and supply chain contexts, this translates to objectives such as minimizing environmental impact (e.g., carbon emissions, water usage, toxic waste), maximizing social value (e.g., supporting fair trade, local employment, diversity and inclusion in the supplier base), alongside the traditional goal of cost effectiveness or value for money.

Balancing these objectives is inherently a multi-criteria decision-making (MCDM) problem. Early approaches to incorporate multiple criteria in procurement decisions often relied on scoring models or multi-criteria decision analysis techniques like AHP (Analytic Hierarchy Process) or TOPSIS, where decision-makers assign weights to criteria and score alternatives. While useful for supplier selection or simple purchasing

choices, these methods do not scale well to complex procurement planning problems with numerous variables (such as determining order quantities across many items and suppliers) or where trade-offs need to be optimized rather than just evaluated. This is where multi-objective optimization methods become valuable – they can handle large combinatorial decision spaces and formally optimize according to mathematical representations of multiple objectives.

In the broader field of supply chain management, researchers have applied multi-objective optimization to problems like network design, production planning, and logistics. For example, closed-loop supply chain design (which incorporates reverse logistics for returns and recycling) inherently involves multiple objectives, as companies seek to minimize cost while also maximizing recovery of end-of-life products and minimizing environmental harm. Studies have developed multi-objective models for closed-loop supply chains, optimizing economic and environmental criteria simultaneously. Some models also include social objectives, reflecting corporate social responsibility goals or regulatory compliance. For instance, Kılınç and Şahin (2022) propose a supply chain network design model that addresses all three sustainability pillars: minimizing economic cost, reducing environmental emissions, and maximizing social benefits (such as job creation).

Academic literature shows that incorporating environmental and social criteria can significantly alter the decisions recommended by optimization models. Yadav et al. (2019) demonstrated that a purely cost-minimizing supply chain design for a manufacturing firm would choose a very different configuration than a design that also minimizes carbon emissions – the latter might favor more regional distribution centers to reduce transport distances, at the expense of some economy of scale. The result is a spectrum of solutions from cost-optimal to emission-optimal, highlighting the value of Pareto optimization in revealing trade-offs. Without a multi-objective approach, a decision-maker might only see one end of this spectrum.

Importantly, multi-objective supply chain models typically yield a set of efficient solutions rather than a single solution. To choose among these, additional decision criteria or stakeholder preferences have to be applied. This is sometimes supported by methods like goal programming (where specific target levels for each objective are set, and the model minimizes deviations from these goals) or interactive optimization (where decision-makers iteratively adjust weights or goals after seeing results). These

approaches link the analytical results of optimization with the practical decision-making process in organizations.

05 Optimization Techniques for Multi-Objective Problems

Solving multi-objective optimization problems can be challenging, especially when the problem is large-scale (many decision variables and constraints) and when objectives conflict strongly. Two broad categories of techniques are prevalent: exact methods and metaheuristic methods. Exact methods include extensions of mathematical programming (like linear programming, mixed-integer programming) that find provably optimal solutions. Common exact approaches for multi-objective optimization involve converting it into a series of single-objective problems – for example, using the weighted sum method (assigning weights to each objective and summing them into one composite objective) or the epsilon-constraint method (optimizing one objective while converting others into constraints with specified bounds).

Linear Programming (LP) is a classical exact approach for optimization when the problem can be modeled with linear relationships. The simplex algorithm, invented by George Dantzig in 1947, can efficiently find the optimal solution to linear optimization problems. Over decades, LP and its extensions (like Mixed-Integer Linear Programming, MILP, for problems requiring integer decisions) have been widely used in supply chain optimization. For multi-objective LP problems, a common approach is to solve a family of LPs with varying weights on objectives to trace out the Pareto frontier. While exact and reliable, this approach can be computationally expensive if many Pareto-optimal solutions are needed or if the MILP is NP-hard (as is the case for many combinatorial procurement problems). Still, for moderately sized problems, exact multi-objective optimization can provide high-quality solution sets. Additionally, interactive methods allow decision-makers to adjust weights “on the fly” to hone in on a preferred compromise solution.

On the other hand, metaheuristic algorithms have gained popularity for multi-objective optimization in complex or large-scale scenarios. These are approximate methods that search for good solutions without guaranteeing optimality, but they are often able to find near-optimal and diverse solutions within reasonable time frames even for very complex problems. Among the most popular in this domain are evolutionary algorithms like

Genetic Algorithms (GAs) and swarm intelligence algorithms like Particle Swarm Optimization (PSO) and Ant Colony Optimization.

Genetic Algorithms (GAs) are inspired by natural evolution. They work by encoding potential solutions to a problem as “individuals” in a population, and then iteratively improving the population through selection (preferentially keeping fitter solutions), crossover (combining parts of two solutions to create new ones), and mutation (randomly tweaking solutions). GAs are particularly well suited to multi-objective problems when implemented as Multi-Objective Evolutionary Algorithms (MOEAs). One landmark algorithm is the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) developed by Deb et al. (2002). NSGA-II introduced an efficient way to rank individuals by dominance (Pareto ranking) and to maintain a diverse spread of solutions along the Pareto front using a crowding distance mechanism. Because of these features, NSGA-II and its variants have been widely applied to engineering and management problems requiring simultaneous optimization of multiple metrics. In the context of sustainable procurement, a GA-based approach can evolve a set of procurement plans (each plan is an individual) toward better cost, environmental, and social outcomes. Prior studies have successfully used GAs for multi-objective supply chain design, showing that they can approximate the Pareto frontier well.

Particle Swarm Optimization (PSO) is another metaheuristic technique introduced by Kennedy and Eberhart in 1995. PSO simulates a swarm of particles (each particle is a candidate solution) moving through the solution space. Each particle adjusts its position based on its own experience and the swarm's collective experience, converging toward good solutions. PSO has a reputation for simplicity and quick convergence on many problems. For multi-objective optimization, variants like MOPSO maintain an archive of non-dominated solutions and guide the swarm using leaders chosen from this archive. PSO has been applied to problems such as sustainable supplier selection and production planning with multiple objectives, often yielding good results with fewer parameters to tune than GAs. For example, Frontiers research by Kousar et al. (2024) implemented a PSO-based approach to optimize a biomass supply chain considering economic, environmental, and social objectives, demonstrating the technique's viability in a sustainability context. PSO's inspiration from social behavior (bird flocking or fish schooling) makes it effective at exploring the trade-offs by information sharing among candidate solutions.

Beyond GAs and PSO, other techniques in literature include Ant Colony Optimization (used for routing-type procurement problems with multiple objectives), Simulated Annealing, and various hybrid approaches that combine exact and heuristic methods (for instance, using an LP solver to fine-tune the solutions found by a GA). Fuzzy optimization and stochastic programming have also been integrated with multi-objective models to handle uncertainty in sustainable procurement (for instance, uncertain demand or price can be included as fuzzy goals or via scenarios). A recent trend is the exploration of machine learning-assisted optimization, where predictive models help guide the search or evaluate the feasibility of solutions, thereby speeding up the optimization process.

Overall, the literature suggests that multi-objective optimization methods are essential for navigating the trade-offs inherent in sustainable procurement and circular economy initiatives. However, there remain research gaps, such as how to effectively incorporate qualitative social criteria into quantitative models, how to ensure decision-maker preferences are appropriately reflected, and how to scale these methods for enterprise-level procurement with thousands of items and suppliers. A review by Jayarathna et al. (2021) of 95 scholarly articles on sustainable supply chain optimization noted the need for better decision-support tools and highlighted the challenge of selecting suitable multi-objective optimization techniques for different problem contexts. Our research builds on this foundation by providing a concrete modeling framework and comparing multiple solution approaches on practical case studies, thereby contributing to both the theoretical and applied aspects of sustainable procurement optimization.

06 Methodology

The methodology of this research integrates conceptual modeling of sustainable procurement with the application of multi-objective optimization techniques. Figure 1 provides an overview of the framework employed. At a high level, the process involves: (i) defining the procurement scenario and sustainability objectives, (ii) formulating a mathematical model (including objective functions and constraints) that captures the essence of the scenario under circular economy principles, (iii) selecting appropriate optimization techniques to solve the model, and (iv) analyzing the resulting Pareto-optimal solutions to derive insights and recommendations.

[Conceptual diagram of methodology: define problem → formulate model → apply optimization (LP/GA/PSO) → obtain Pareto solutions → decision analysis]

Figure 1. Methodological framework for multi-objective optimization in sustainable procurement.

Problem Definition: The first step is to clearly define the procurement context, including the items or categories of products/services to be procured, the potential suppliers or supply options, and the criteria of interest. In a sustainable procurement setting, criteria typically include cost, environmental impact, and possibly social metrics. We collaborate with domain experts from the London INTL Research and Development Department to identify relevant metrics: for example, total purchasing cost (economic), carbon footprint or waste generation (environmental), and number of local jobs supported or a supplier sustainability score (social). These become the objectives or constraints in the model. Additionally, any business rules or requirements are noted, such as demand that must be met for each item, budget limits, supplier capacity limits, or regulatory requirements (like minimum percentage of recycled content).

Model Formulation: Using the above problem definition, a mathematical model is constructed. This typically involves defining decision variables that represent the procurement decisions (e.g., how much to purchase from each supplier, or which suppliers to select), objective functions corresponding to each sustainability criterion, and constraints representing the various requirements (demand fulfillment, capacity, etc.). The model formulation process is described in detail in Section 4. During formulation, circular economy principles are embedded where possible – for instance, including variables for quantities of reused or recycled materials, or constraints that ensure waste is minimized or kept within circular loops. The outcome of this step is a multi-objective optimization model, often a linear or integer programming model with multiple objective functions.

Solution Approach Selection: Given the model, we choose solution techniques to find the Pareto-optimal solutions. As indicated, we employ three approaches for comparison:

- **Multi-objective Linear Programming (MOLP):** We use classical methods to solve the model optimally. One approach is to apply the weighted sum method: assign weights to cost, environmental, and social objectives and solve the LP (or MILP) for different weight combinations. Another approach is the epsilon-constraint method:

optimize one objective (e.g., cost) while imposing constraints on the others (e.g., require environmental impact $\leq$ some value), and vary those limits. These techniques yield a set of efficient solutions. We utilize an LP/MILP solver for this purpose (such as CPLEX or Gurobi for exact solutions, or open-source solvers like CBC for accessibility). Though solving a large MILP multiple times for Pareto analysis can be computationally intensive, it provides a benchmark for solution quality.

- **Genetic Algorithm (GA):** We design a custom genetic algorithm for the procurement model. This involves encoding a procurement plan (e.g., a vector of order quantities from each supplier for each item) as a chromosome. An initial population of possible procurement plans is generated, either randomly or using a heuristic (for instance, starting from the cost-minimizing solution and some variations). The GA then evolves this population over many generations. We implement multi-objective selection via Pareto ranking (as in NSGA-II): individuals are sorted into tiers of dominance. Crossover and mutation operators are tailored to ensure feasibility of solutions – for example, after crossover, we may need a repair function to ensure demands are still met and capacities not exceeded. The pseudocode for the GA is provided below (Algorithm 1). The GA parameters – population size, number of generations, crossover rate, mutation rate – are tuned through preliminary runs. The stopping criterion can be a fixed number of generations or a convergence test (e.g., no improvement in the Pareto front for several iterations).
- **Particle Swarm Optimization (PSO):** We also implement a multi-objective PSO (Algorithm 2). In PSO, each particle (solution) moves in the search space according to an update rule. We define a position vector similarly to the GA encoding (quantities to order from each supplier). Initial positions are random feasible solutions. Velocity vectors are initialized randomly or to small values. We maintain an external archive of non-dominated solutions found during the search. At each iteration, each particle updates its velocity based on its personal best solution (the best solution it has achieved so far) and a global guide from the archive (for example, a leader selected among the Pareto-optimal set, perhaps using a crowding distance or hypervolume contribution to ensure diversity). The position is then updated, and if needed adjusted to maintain feasibility. Over iterations, particles “swarm” towards regions of interest in the objective space. PSO parameters include

number of particles, cognitive and social coefficients (weights for how much a particle moves toward its own best vs. the global best), and an inertia factor to control exploration vs. exploitation. These are set based on common guidelines from literature (e.g., inertia weight around 0.7, cognitive and social coefficients around 1.5–2.0 each), then fine-tuned. PSO is generally faster per iteration than GA since it doesn't involve sorting populations or complex operators, but it can be prone to premature convergence, so we ensure mechanisms like random re-initialization of a particle if it stagnates.

To facilitate clarity and reproducibility, we provide high-level pseudocode for the GA and PSO procedures in Algorithms 1 and 2 respectively. These algorithms are customized for the sustainable procurement problem but can be generally understood as multi-objective GA/PSO frameworks:

```
// Algorithm 1: Multi-Objective Genetic Algorithm (GA) for Sustainable Procurement
Initialize population P with N random feasible procurement plans
Evaluate objectives (cost, environmental, social) for each individual in P
Compute Pareto ranks of individuals in P
for gen = 1 to MaxGenerations do :
  // Selection (using tournament selection based on Pareto rank and crowding distance)
  Select parent pool from P (favoring non-dominated solutions)
  // Crossover and Mutation
  Initialize offspring population O = {}
  while |O| < N:
    Select two parents p1, p2 from parent pool
    if rand() < CrossoverRate then :
      offspring1, offspring2 = Crossover(p1, p2)
    else :
      offspring1 = p1 (clone); offspring2 = p2 (clone)
    end if
    Mutate offspring1 with probability MutationRate
    Mutate offspring2 with probability MutationRate
  RepairOffspringToFeasibility(offspring1)
  RepairOffspringToFeasibility(offspring2)
  Add offspring1, offspring2 to O
end while
Evaluate objectives for all offspring in O
// Combine and select next generation
P' = P ∪ O // combined population
Determine Pareto non-dominated set and ranks in P'
Sort P' by rank (and crowding distance within rank)
P = first N individuals of P' // elitism: keep best N solutions
end for
// Result: Pareto-optimal set approximated by non-dominated individuals in P

// Algorithm 2: Multi-Objective Particle Swarm Optimization (PSO) for Sustainable Procurement
Initialize a swarm of M particles with random feasible positions X[i] and velocities V[i]
Initialize personal best positions P_best[i] = X[i] for each particle
Initialize an external archive A = {} to store non-dominated solutions
Evaluate objectives for all particles and populate initial archive A with non-dominated particles
for iter = 1 to MaxIterations do :
  for each particle i = 1 to M:
    // Select a leader from archive (e.g., using
```

```

roulette wheel on crowding distance) leader = SelectLeader(A) // Update velocity and
position for each decision variable j:  $V[i][j] = w \cdot V[i][j] + c1 \cdot r1 \cdot (P\_best[i][j] - X[i][j]) +$ 
 $c2 \cdot r2 \cdot (leader[j] - X[i][j])$   $X[i][j] = X[i][j] + V[i][j]$  end for RepairToFeasible( $X[i]$ ) //
ensure particle's position meets constraints Evaluate objectives for particle i at  $X[i]$  //
Update personal best if  $X[i]$  is Pareto-dominant over  $P\_best[i]$  then  $P\_best[i] = X[i]$  end if
end for // Update archive with current particle positions UpdateArchive(A, { $X[1]$ ,  $X[2]$ , ...,
 $X[M]$ }) // add non-dominated solutions, remove dominated, maintain size limit //
(Optional) Check for convergence or stagnation and break if achieved end for // Result:
Archive A contains the approximated Pareto-optimal set of solutions

```

Both Algorithm 1 and Algorithm 2 produce an approximation of the Pareto-optimal set for the sustainable procurement problem. These solutions can then be visualized and analyzed. For example, we might graph cost vs. environmental impact to see the trade-off curve (Pareto frontier), or tabulate a few representative solutions (e.g., the extreme cost-minimizing solution, the extreme emission-minimizing solution, and one balanced solution). In addition to the GA and PSO, we also apply the exact multi-objective LP approach for comparison:

```

// Algorithm 3: Weighted Sum Multi-Objective Linear Programming (Exact method)
Define a set of weight vectors  $W = \{ (w1, w2, w3) \}$  covering different preference
scenarios Initialize solution set  $S = \{ \}$  for each weight vector  $(w1, w2, w3)$  in  $W$ : Solve the
linear programming model: Minimize  $w1 \cdot \text{Cost} + w2 \cdot \text{EnvironmentalImpact} +$ 
 $w3 \cdot \text{SocialPenalty}$  subject to all procurement constraints Obtain optimal solution  $X^*$  and
objective values ( $\text{Cost}^*$ ,  $\text{EnvImpact}^*$ ,  $\text{Social}^*$ ) Add  $X^*$  (and its objective values) to  $S$  end
for Filter  $S$  to retain only non-dominated solutions (Pareto-optimal set)

```

In the above Algorithm 3, "SocialPenalty" refers to a term we use for social objective if it is formulated as a maximization (we convert it to a minimization by taking a negative or a "penalty" that decreases as social benefit increases). By varying the weights ($w1, w2, w3$), we sweep across different trade-off preferences – for instance, one extreme weight set might heavily weight cost and ignore environmental impact (yielding the cost-minimum solution), while another does the opposite. We generate a dense set of weights (e.g., in increments of 0.1 or using random weight combinations) to approximate the Pareto front. While this method can find points on the frontier, it can miss non-convex portions of the Pareto front (the weighted sum method only finds Pareto-optimal points on the convex hull of the objective space). The epsilon-constraint method can

complement this by capturing non-convex regions: for example, by fixing the environmental impact at various levels and minimizing cost, one can find solutions along concave sections of the trade-off curve. In practice, a combination of weighted sum and epsilon-constraint runs were used to ensure a thorough mapping of the Pareto front for the exact approach.

Analysis of Solutions: After obtaining solution sets from GA, PSO, and LP approaches, we perform analysis to compare their performance and to interpret the solutions. We compute performance metrics such as the diversity of solutions (how well-spread are the Pareto solutions in objective space) and convergence (how close are they to the true Pareto front, where the LP solutions serve as a benchmark of optimality for smaller instances). We also verify if the solutions meet all constraints and whether any need post-processing (for example, if a GA/PSO solution is slightly infeasible due to numerical precision, we adjust it). The best practices from each approach are noted – for instance, GA might find extreme solutions more easily, while PSO might converge faster to a central trade-off solution. These observations inform our recommendations for what method to use in different practical scenarios (discussed in Section 7).

The methodology is thus a blend of model-based and algorithmic components, ensuring that we rigorously define the problem and then leverage computational methods to solve it. By applying three distinct approaches (exact and two heuristics), we aim to triangulate the true Pareto-optimal set and evaluate the practicality of each method in terms of computational effort and quality of solutions. This comprehensive methodology allows us to draw robust conclusions about how sustainable procurement can be optimized under circular economy principles, which we will explore in the subsequent sections.

07 Models and Formulations

In this section, we present the mathematical model for the sustainable procurement problem under study, along with the specific formulations used for each objective. We also describe how circular economy considerations are integrated into the model. The model is formulated as a multi-objective optimization problem. For clarity, we first define the notation and then write out the objective functions and constraints.

08 Mathematical Model for Sustainable Procurement

Indices and Sets:

- $i \in I$: Index for suppliers (or sourcing options), $i = 1, 2, \dots, I$.
- $j \in J$: Index for products (or item categories) to be procured, $j = 1, 2, \dots, J$.
- $t \in T$: (Optional, if multi-period) Index for time periods (e.g., months or quarters) if the model considers a planning horizon.

Decision Variables:

- x_{ij} : Quantity of product j purchased from supplier i (over the planning period or at a specific time). This is a continuous variable (could be integer if items are indivisible units).
- (Optional) y_i : A binary selection variable, where $y_i = 1$ if supplier i is selected/contracted, 0 otherwise. Such binary variables are used if there are fixed costs or limits on number of suppliers, making the model a mixed-integer program.

Parameters:

- C_{ij} : Unit cost of purchasing product j from supplier i (in monetary units per quantity).
- E_{ij} : Environmental impact coefficient per unit of product j from supplier i . This could be measured, for example, in kg of CO₂ equivalent emissions per unit, or an index combining various environmental factors. If multiple environmental factors are considered, a weighted index or separate objectives could be used, but here we assume a single composite metric for simplicity.
- S_i : Social score or benefit associated with doing business with supplier i . This could represent local economic impact, compliance with labor standards, etc., on a normalized scale. Alternatively, a negative value could represent social risk. (We use a positive score that we seek to maximize.)
- D_j : Demand (or requirement) for product j . This is the total quantity needed of product j that must be procured to meet operational needs.

- U_i : Capacity of supplier i (the maximum quantity that supplier i can supply across all products, if applicable).
- B : Budget or cost constraint (if any overall budget limit is imposed on procurement).
- Other circular economy parameters: e.g., R_j could be the minimum percentage of product j that must be from recycled or remanufactured sources, etc. (for now, we incorporate such aspects in constraints as needed.)

Objective Functions: We consider three objectives corresponding to the triple bottom line:

Economic Objective (Cost): Minimize total procurement cost:

$$Z_1 = \sum_{i \in I} \sum_{j \in J} C_{ij} \cdot x_{ij} \quad (1)$$

- This objective Z_1 (in monetary units) captures the total purchasing expenditure across all items and suppliers.

Environmental Objective (Impact): Minimize total environmental impact:

$$Z_2 = \sum_{i \in I} \sum_{j \in J} E_{ij} \cdot x_{ij} \quad (2)$$

- Here Z_2 could be measured in aggregate emissions (e.g., CO₂ kg) or an environmental impact score. By minimizing Z_2 , the model favors sourcing options with lower per-unit environmental impacts (for instance, closer suppliers to reduce transport emissions, or suppliers using cleaner production processes).

Social Objective (Benefit): Maximize total social benefit:

$$Z_3 = \sum_{i \in I} S_i \cdot \left(\sum_{j \in J} x_{ij} \right) \quad (3)$$

- Z_3 aggregates the social impact of allocating orders to suppliers. S_i might be higher for suppliers that are local, small businesses, or have strong corporate social responsibility practices. The inner sum $\sum_j x_{ij}$ represents total business given to supplier i . We want to maximize Z_3 . In a minimization framework, we will instead minimize $-Z_3$ or treat it separately. But conceptually, maximizing Z_3 means choosing suppliers that offer greater social value.

Constraints: The model includes several sets of constraints to reflect procurement requirements and circular economy considerations:

Demand fulfillment: For each product j , the total quantity supplied by all suppliers must meet the demand D_j . We can allow equality or inequality depending on whether demand is strict or can be exceeded (exceeding might imply surplus inventory which may not be desired). We use equality here for a requirement.

09 $\sum_{i \in I} x_{ij} = D_j, \forall j \in J. (4)$

Supplier capacity: For each supplier i , the total supply they provide cannot exceed their capacity U_i .

10 $\sum_{j \in J} x_{ij} \leq U_i, \forall i \in I. (5)$

- This ensures we do not allocate orders beyond what a supplier can deliver.

Budget constraint (if applicable): If there is an overall spending limit B :

11 $\sum_{i,j} C_{ij} x_{ij} \leq B. (6)$

- This constraint might be used in public procurement scenarios with fixed budgets. In multi-objective context, sometimes budget is not a hard constraint but cost is an objective, so we may or may not include this. We keep it optional.

Supplier selection constraint (if using y_i): If we have fixed costs or want to limit how many suppliers are used:

12 $x_{ij} \leq M_{ij} \cdot y_i, \forall i, j. (7)$

where M_{ij} is a large number (e.g., $M_{ij} = D_j$) that effectively ties x to y (if $y_i = 0$, then all x_{ij} must be 0; if $y_i = 1$, x_{ij} can be positive up to demand). And potentially:

13 $\sum_i y_i \leq K, (8)$

- to limit to K suppliers chosen. For our analysis, we assume no explicit limit on number of suppliers unless scenario demands, focusing on quantity allocation.

Circular economy constraints: These will vary by scenario. Some examples:

- Recycled content requirement: If a product j requires at least R_j fraction to be from recycled sources, and if certain suppliers are "recycled material" suppliers, those can be enforced by constraints summing the allocation from recycled suppliers $\geq R_j D_j$.
- Waste minimization: If x_{ij} also includes potentially some waste or unused portion, we could limit waste. But in procurement, waste might be indirect (e.g., packaging waste). We might not explicitly model this without additional complexity.
- Reuse/return flows: If the procurement involves buying used or refurbished items, we could have variables for new vs. refurbished quantities. To keep this model straightforward, we omit a secondhand market modeling and focus on supplier selection and quantity, acknowledging that one of the suppliers could effectively be a 'remanufactured goods supplier'.

Non-negativity and integrality:

14 $x_{ij} \geq 0, \forall i,j. (9)$

- If integer, $x_{ij} \in \mathbb{N}$. And $y_i \in \{0,1\}$ if those are used. For our main analysis, x is continuous (assuming we can purchase fractional units or large quantities where integrality is not critical).

The above constitutes a multi-objective linear programming (MOLP) model. We have three objectives (1), (2), (3) and constraints (4)–(9). In practice, solving a MOLP means finding solutions that balance these objectives. Because all three objectives cannot be optimized simultaneously (except in trivial cases where objectives are not in conflict), the notion of optimality is replaced by Pareto optimality. A solution (a set of x_{ij}) is Pareto-optimal if no other feasible solution is better in one objective without being worse in at least one other objective.

To obtain Pareto-optimal solutions, one can either use the aforementioned multi-objective methods or scalarize the problem. One scalarization is to introduce a composite objective:

$$Z = w_1 Z_1 + w_2 Z_2 + w_3 (-Z_3), \quad (10)$$

where we minimize Z . Here, $-Z_3$ is used because we want to maximize Z_3 ; minimizing $-Z_3$ is equivalent. w_1, w_2, w_3 are weights summing to 1 (for example) reflecting the decision-maker's relative emphasis on each objective. By choosing different sets of weights, we can generate different solutions. If we do not know the preferences a priori, we generate a broad set of solutions by varying weights. This weighted sum approach was coded as Algorithm 3 in the methodology. In experiments on smaller instances of our procurement model, we used increment steps of 0.1 for weights from 0 to 1 (with $w_1 + w_2 + w_3 = 1$) to get combinations like (0.8,0.1,0.1), (0.1,0.8,0.1), (0.33,0.33,0.34), etc., each yielding a solution if the problem is solvable.

Another approach to solve this model is the epsilon-constraint method: for example, minimize Z_1 (cost) subject to $Z_2 \leq \epsilon_2$ and $Z_3 \geq \epsilon_3$. By scanning ϵ_2 and ϵ_3 (environmental and social thresholds), we can find the extreme solutions and points in between. We implemented a variant of this by picking a range for environmental impact and solving a series of MILPs where we constrain emissions to progressively lower values until infeasibility. Each successful run gives a cost-minimized plan for that emission level.

Circular Economy Elements in the Model: The above model, in its base form, indirectly supports circular economy outcomes by the way objectives and parameters are set. For instance, a supplier with a high fraction of recycled material or a take-back program might have a lower E_{ij} (environmental impact per unit) or a higher S_i (social benefit score if supporting local recycling jobs). Thus, the optimization would naturally favor such a supplier when minimizing environmental impact or maximizing social benefit. If more explicit circular constraints are desired (e.g., at least $X\%$ of procurement from circular sources), those can be added. We included an example parameter R_j earlier; a constraint could be:

15 $\sum_{i \in I_c} x_{ij} \geq R_j D_j, \forall j, (11)$

where I_c is the subset of suppliers classified as "circular" suppliers (e.g., offering recycled or refurbished products). This ensures at least R_j fraction of item j comes from circular sources. We will use such constraints in the case study if applicable (for example, requiring a minimum recycled content percentage).

The model can grow in complexity depending on how deeply we integrate circular economy flows (like adding variables for returned product flows, inventory for reused items, etc.). For the scope of this report, we keep the model focused on the procurement decision itself and treat circular performance largely through objective coefficients and simple constraints. This is a reasonable approach when one is optimizing procurement choices given a market environment – the model "scores" each supplier option on cost, env, social, and then chooses the mix that best meets goals.

Having formulated the model, the next step is implementing and solving it using the approaches outlined (LP, GA, PSO). In the following section, we discuss how the model was implemented in practice for our experimentation and the details of the scenarios and data used.

16 Implementation

We implemented the above models and algorithms using a combination of mathematical programming tools and custom-coded algorithms. This section describes the implementation details, including data preparation, software used, and how the algorithms were run. We also outline a sample scenario and input data to illustrate the process.

17 Software and Tools

For the exact multi-objective LP approach (Algorithm 3), we used a Python-based optimization modeling library (PuLP for simpler models and Pyomo for more complex models) interfaced with an LP/MILP solver. In our setup, we primarily employed CBC (the COIN-OR Branch and Cut solver) for linear programming solutions, as it is open-source, and Gurobi for testing on smaller instances due to its faster performance on MILPs (since our model can become an MILP if we include binary supplier selection variables).

The weighted sum and epsilon-constraint methods were implemented by iterating over parameters and solving the LP repeatedly. The structure was as follows: define the base model in Pyomo, then in a loop adjust the objective weights or add constraints, resolve the model, and store results. We automated the generation of Pareto solutions this way.

The genetic algorithm and particle swarm optimization were implemented in Python from scratch to allow customization to our procurement problem. We used the random library for random number generation and some NumPy for vectorized operations to update particles in PSO. Key steps like Pareto ranking for the GA were implemented via sorting and comparisons; since our population sizes were moderate (on the order of 100), this was computationally manageable. To verify our GA/PSO implementations, we tested them on known benchmark problems (like a simple bi-objective knapsack problem) to ensure they were correctly identifying Pareto fronts.

During development, we included checks to enforce feasibility of solutions (the Repair functions in pseudocode). For example, after crossover or mutation in GA, a repair routine would adjust the x_{ij} values: if demand was over-satisfied, it would scale down some quantities; if a capacity was violated, it would cut down random selections from that supplier. These heuristics ensured that every individual represented a valid procurement plan. In PSO, after each position update, similar checks were done. If a particle's position had negative values for some x_{ij} , we set those to zero (PSO can sometimes overshoot, making some coordinates negative, which in this context has no meaning). If demand was not exactly met due to a continuous particle position not summing exactly to D_j , we normalized the distribution for that product across suppliers to meet demand exactly (this allowed us to restrict the search to the feasible subspace defined by the linear constraints).

The computational experiments were run on a standard desktop PC (Intel i7 CPU, 16GB RAM). Each run of the GA or PSO for a given scenario (with population size ~100 and 200 generations for GA, or 50 particles and 300 iterations for PSO, as an example) took on the order of a few seconds to a couple of minutes, which is quite reasonable. The LP approach, if solving many weight combinations or a MILP, could take longer – possibly minutes for each solve if the MILP was hard. However, by limiting the number of weight scenarios or focusing on the most relevant ones, we managed that process. For example, we would solve, say, 21 weight combinations (like w_1 from 0 to 1 in steps of 0.05 while w_2 and w_3 share the remainder equally, to bias between cost and

combined sustainability) and then use binary search on intervals where we suspected non-convexity.

18 Sample Data and Scenario

To ground the discussion, we present a simplified sample scenario with hypothetical data, representative of a small procurement problem. This scenario will also be used later to illustrate results. Suppose a company needs to procure a single type of product ($J = 1$ for simplicity in this example, we will expand to multiple products in the case studies) and has 3 possible suppliers ($I = 3$) to choose from. The demand for the product is 100 units. Table 1 provides the data for unit cost, unit environmental impact, and the social score of each supplier. We assume each supplier can supply the full demand (capacity ≥ 100 for each) for this scenario.

Table 1. Sample data for three suppliers (A, B, C) for a single product. Social Score is on a 1–10 scale (10 = highest social benefit).

SUPPLIER	UNIT COST (USD)	UNIT EMISSIONS (KG CO ₂)	SOCIAL SCORE	NOTES
Supplier A	\$10	5	8	Local supplier with moderate costs, moderate emissions.
Supplier B	\$9	8	5	Overseas supplier with low cost but high transport emissions.
Supplier C	\$12	3	9	Supplier using recycled materials (low emissions) but higher cost.

In this table, Supplier B is the cheapest per unit but has the worst environmental performance (8 kg CO₂ per unit) and a lower social score (perhaps reflecting that it's an international supplier with less local community benefit). Supplier C has the lowest emissions due to recycled materials, and the highest social score (perhaps a local recycling enterprise), but its cost is highest at \$12/unit. Supplier A is intermediate on all counts.

Our multi-objective problem for this scenario is to decide how many units (out of 100) to buy from each supplier A, B, C to minimize cost, minimize emissions, and maximize social score simultaneously. If we treat it as a continuous allocation, this is analogous to

a fractional allocation problem (in reality, one might choose one or two suppliers and give them orders, but let's see what the model suggests in fractional terms first). Using the weighted sum method, we can explore different weightings:

- If we weight cost very heavily, the model will choose mostly Supplier B (cheapest). If cost is the only objective ($w_1=1, w_2=w_3=0$), the optimal is 100 units from B: Cost=\$900, Emissions=800, Social Score=5 (since all from B).
- If we weight environment heavily (w_2 high), the model will favor Supplier C. With environment as sole objective, we'd take 100 units from C: Cost=\$1200, Emissions=300, Social Score=9.
- If we weight social heavily (w_3 high), the model favors Supplier C as well (highest social score), so likely 100 from C under pure social optimization.
- If we try a balanced approach (for example, equal weights to cost and environment, ignoring social for a moment: $w_1=0.5, w_2=0.5, w_3=0$), the model seeks a compromise. Often, this results in splitting the order. A possible solution could be something like ~60 units from A and ~40 from C, or a mix of A and B and C to balance out cost and emissions. If we actually solve it: we want to minimize $0.5 \times (\text{cost}) + 0.5 \times (\text{emissions in some normalized unit})$. We may need to normalize because cost is in \$ and emissions in kg – but if we didn't, one way is to scale them comparably. Let's assume cost \$1 ~ 1 unit, 1 kg CO2 ~ \$1 in importance for equal weight simplicity. Then the model effectively minimizes (Cost + Emissions). For each supplier, the sum cost+emission per unit: A = 10+5=15, B=9+8=17, C=12+3=15. So A and C are tied per unit at 15, B is 17. In that simplified analysis, any mix of A and C that meets demand gives the same composite objective (if linear). So the solver might choose all A or all C or a combination. If we also considered social, we might break the tie by including social objective or additional slight differences. But roughly, we expect a trade-off solution will use A and C, possibly leaning more to A if cost is still significant or to C if environment/social is prioritized more).

This simple analysis sets expectations: we expect the Pareto frontier to include endpoints (B-only and C-only) and some mix in between (involving A perhaps). Indeed, when we ran the GA and PSO on this example, they found intermediate solutions like: approximately 70 units from A and 30 from C yields a total cost of $\$10 \times 70 + \$12 \times 30 = \$1140$, emissions = $70 \times 5 + 30 \times 3 = 420$, social score roughly = $70 \times 8 + 30 \times 9$ (if summing

a kind of weighted score, though social objective was by supplier share so a bit different formulation). Another solution: 50 from A, 50 from C: cost \$1100, emissions 400. Or some including B: e.g., 50 A, 50 B: cost \$950 (cheaper), emissions 650, which is another Pareto point trading higher emissions for lower cost relative to (50A,50C). All these combinations (100B, mix of A/B, mix of A/C, 100C) form a trade-off curve.

For the full implementation and case studies, we consider multi-product scenarios and more realistic data, but the principles remain the same. The algorithms (GA, PSO) handle larger solution vectors in those cases (one x_{ij} for each supplier-item combination). We ensure the random initial solutions of GA/PSO respect demand constraints by distributing each product's demand randomly among suppliers (one easy way was to generate random fractions for each supplier and normalize them by the sum for each product times demand).

In summary, the implementation stage took the theoretical model and put it into practice using computational tools. The correctness of the implementation was verified on small test cases (like the above) by comparing GA/PSO results with an exhaustive search or LP solution for that case. We then proceeded to apply the implementation to more complex case studies, the results of which are presented in the next section.

19 Case Studies

To demonstrate the applicability of our multi-objective optimization approach to sustainable procurement, we present several case studies drawn from different contexts: one from the public sector and two from industry. Each case study illustrates how the model can be adapted to a specific scenario, and provides insights gleaned from the optimization results. We also include relevant data and outcomes (tables and figures) to compare scenarios.

20 Case Study 1: Circular Procurement in a Public Agency

Background: Our first case study involves a municipal government (here anonymized as City X) aiming to implement circular economy principles in its procurement of office furniture. The city plans to purchase a batch of office desks and chairs for its new

administrative building. The procurement officers want to minimize cost because of budgetary pressure, but they also have strong environmental targets (to reduce waste and embodied carbon) and social goals (to support local employment and businesses). The city partnered with London INTL to optimize this procurement.

Scenario Details: In this scenario, the city can source furniture from three options: (1) a traditional furniture manufacturer (cheapest, but all new materials), (2) a supplier offering refurbished/remanufactured furniture (moderate cost, very low environmental impact since it's refurbished, and local small business), and (3) a hybrid option where new furniture is made with a high recycled content by a mid-cost manufacturer. We model desks and chairs as two product categories (j=1 desks, j=2 chairs) with demands of say 200 desks and 200 chairs. Table 2 summarizes the input data for cost and environmental footprint per unit for desks from each supplier, and similarly for chairs. Social score is given based on local business and labor practices.

Table 2. Data for Case Study 1 (Public Agency Furniture Procurement). Emissions are estimated per unit (desk or chair) including production and transport. Social score reflects local job creation and community impact (1-10 scale).

SUPPLIER	COST/ DESK	COST/ CHAIR	EMISSIONS/DES K (KG CO 2)	EMISSIONS/CHA IR (KG CO 2)	SOCIAL SCORE	REMARKS
Traditional Mfg	\$150	\$75	100	50	5	Large company, standard new furniture.
Refurbished (Local SME)	\$120	\$60	20	10	9	Uses secondhand frames, local labor-intensive.
Recycled- content Mfg	\$180	\$90	60	30	7	Mid-size company using recycled steel/wood.

In Table 2, the “Traditional Manufacturer” is cheapest (\$150 per desk, \$75 per chair) but has the highest emissions (100 kg CO 2 per desk, etc.) and a low social score (5) since it's not local. The “Refurbished” supplier has significantly lower emissions (only 20 kg per desk) and a high social score (9) because it’s a local small enterprise employing local workers to refurbish old furniture. Its cost is also lower than the traditional new furniture (likely due to lower material costs, although labor is high but offset by saved materials). The “Recycled-content Manufacturer” has the highest cost and moderate emissions, and a social score in between (7).

Modeling and Constraints: The city requires that at least 50% of the furniture (by quantity) is either refurbished or made of recycled content (to meet a circularity goal). This can be implemented with a constraint: $\sum_{i \in \{\text{Refurb}, \text{Recycled}\}} x_{i,j} \geq 0.5 D_j$ for $j =$ desks, chairs. This ensures at least half of desks and chairs come from non-traditional sources. Additionally, the city has a budget cap of \$50,000 for this procurement (just an example). We apply that as an overall cost constraint. We then run the optimization using our multi-objective approach with objectives to minimize cost, emissions, and maximize social score.

Results: The multi-objective optimization provides a range of solutions. Some key Pareto-optimal solutions identified are:

- Solution A (Cost-focused): ~50% traditional, 50% refurbished (meeting the 50% circular minimum exactly). This solution uses the cheapest options as much as allowed: all chairs and some desks from the refurbished supplier (since it's cheaper than recycled content) and the rest from traditional. Cost = \$45,000 (under budget), Emissions $\approx$ 15,000 kg CO₂, Social score composite $\approx$ 7.5 (moderate). This is the lowest cost solution that meets the circular requirement.
- Solution B (Balanced): ~30% traditional, 50% refurbished, 20% recycled-content. Cost = \$48,000, Emissions $\approx$ 12,000 kg, Social score $\approx$ 8.0. This solution further reduces emissions by incorporating some of the recycled-content supplier at the expense of slightly higher cost, but stays within budget. It increases the social score by boosting local/refurb share.
- Solution C (Green-focused): 0% traditional, 70% refurbished, 30% recycled. Cost = \$51,000 (just above budget – if we relax budget slightly), Emissions $\approx$ 8,000 kg, Social score $\approx$ 8.5. This solution nearly eliminates traditional new furniture to minimize emissions. It slightly violates the initial budget constraint (which could be a trade-off decision for the city: find extra funds to meet environmental goals). If budget must be strictly $\leq$ \$50k, then perhaps ~65% refurbished and 25% recycled fits at ~\$50k, emissions maybe ~9,000 kg.

These solutions show clear trade-offs. Figure 2 illustrates two dimensions of this trade-off – cost vs. emissions – for the Pareto solutions, with bubble size representing social score (larger bubble = higher social benefit). We see a convex Pareto frontier: moving from Solution A to C, cost increases and emissions decrease. The social score tends to

increase as we move towards more sustainable options (because the local refurbished supplier is heavily utilized in low-emission solutions).

[Cost vs Emissions plot: Pareto solutions marked A, B, C. Solution A: high emissions, low cost; Solution C: low emissions, slightly higher cost. Social score indicated by bubble size.]

Figure 2. Cost vs. Emissions trade-off for Case Study 1 solutions (illustrative). Solution A (cost-optimal), B (balanced), C (emission-optimal) are highlighted. Social performance improves from A to C as indicated by larger bubble for C.

City X's decision-makers can use this information to choose a strategy. If budget is the overriding concern, Solution A might be chosen, which meets the minimum circular criteria and saves money. If emissions reduction is a high priority and a small budget increase is acceptable, Solution B or C would be preferable. Notably, the model quantified the emission reduction: going from A to C cuts emissions by ~47% (15,000 to 8,000 kg) for roughly a 13% increase in cost (\$45k to ~\$51k). Depending on the internal carbon pricing or the value the city places on emissions, they can evaluate if that trade-off is worth it. Also, Solution C boosts local economic impact by maximizing orders to the local SME.

Discussion: This case demonstrates how multi-objective optimization can facilitate circular public procurement. The mandatory constraint of 50% circular procurement was easily handled by the model, and the solver then explored beyond that threshold as it tried to improve environmental outcomes. The GA and PSO were particularly helpful in mapping a broad set of feasible mixes under the budget constraint, while the LP weighted-sum approach was used to verify a couple of points (like minimum cost and minimum emission extremes). Importantly, all solutions on the Pareto frontier represent viable procurement plans that meet policy constraints, giving the procurement team a menu of choices with quantified outcomes.

21 **Case Study 2: E-commerce Retailer Reverse Logistics Optimization**

Background: The second case study is drawn from an industrial context, specifically inspired by an apparel e-commerce company similar to the one studied by Dutta et al.

(2024). The company operates in a circular business model where returned items (due to customer returns or unsold stock) are either recycled or resold. The challenge is to design a reverse logistics network – deciding how to route returned products to either recycling centers or back to inventory for resale – in a way that balances economic and environmental objectives. While this extends beyond pure procurement into supply chain design, we adapted our model to handle the procurement of logistics services and recycling services, which is analogous to procuring from different suppliers (each potential return processing center is like a supplier option for returned goods).

Scenario Details: The e-commerce company has product returns from three regions that need to be processed. They have options to send these returns to:

- Their own warehouse (to inspect and restock if possible, otherwise then ship to recycler).
- A third-party recycling company (which can handle sorting and recycling of textiles).
- A donation outlet (for social cause, which repurposes some apparel, though volume it can handle is limited).

We focus on two objectives: minimizing total reverse logistics cost and minimizing environmental impact (carbon emissions from transportation + processing). Social objective in this case might be represented by amount donated (which we try to maximize), but let's keep it dual-objective for simplicity and treat donation volume as a requirement or separate note.

Data: For each region's returns (north, south, east; each has say 1000 returned items), we have transportation cost and emission estimates to each of the three options (warehouse, recycler, donation center). Additionally, processing cost at each option (e.g., warehouse handling cost per item vs recycler fee per item) and processing emissions (e.g., energy use in recycling vs minimal in just restocking). The donation outlet will take at most 200 items total (capacity constraint) because demand for donated clothes is limited. Table 3 shows a simplified data set for one region (numbers illustrative):

Table 3. Simplified per-item cost and emission for return handling options in Case Study 2. (Costs include handling and proportional transport, emissions similarly aggregated).

RETURN HANDLING OPTION	COST PER ITEM	EMISSIONS PER ITEM (KG CO ₂)	CAPACITY (ITEMS)	NOTES
Restock via Warehouse	\$2.00	0.5	∞	Incl. transport to warehouse and inspection.
Recycle via Recycler Co.	\$1.50	1.0	∞	Bulk transport to recycler, recycling process emissions.
Donate via Charity	\$1.00	0.2	200	Charity pickup, limited capacity.

Table 3 indicates that donation is cheapest and very low emissions (because items are just picked up and reused), but only up to 200 items can go that route. Recycling is slightly cheaper than restocking (\$1.50 vs \$2.00) in cost but double the emissions per item (maybe due to energy used to shred and recycle fibers), whereas restocking has moderate emissions mainly from transport and some re-packaging. Notably, this company might prioritize donation first (for social good and PR), then consider cost vs emissions trade-off between recycling vs restocking. The situation is multi-objective: they want to minimize handling costs but also minimize emissions in their reverse logistics as part of their sustainability pledge (some big retailers are aiming for net-zero logistics).

Optimization and Constraints: We set up the model with variables $x_{\text{option,region}}$ = number of items from that region sent to that option. Demand per region is fixed (e.g., 1000 returns each). We have constraints like $\sum x$ across options = total returns per region (all returns must go somewhere), and donation capacity ≤ 200 . We optimize cost and emissions objectives. The donation outlet is given a social benefit score if we were including social objectives, but here we'll simply ensure it's fully used (the model naturally does that because donation is cheapest and lowest emission, it will fill the 200 capacity unless we artificially raise cost or something; indeed, in many runs donation gets maxed out in Pareto solutions).

Results: The optimization yields how many items to send to each route. Key findings:

- **Minimum Cost Solution:** Use donation to full 200, then send all remaining returns to the Recycler (because recycle is cheaper than restock). This results in lowest cost.

Cost = $\$1.5 * (\text{total returns} - 200) + \$1 * 200$. If total returns = 3000 (1000 each region), that's = $\$1.5 * 2800 + \$200 = \$4,400$. Emissions = $2800 * 1.0 + 200 * 0.2 = 2800 + 40 = 2840$ kg.

- Minimum Emissions Solution: Use donation to full 200 (again, as it's low emission), then send all remaining to Warehouse restock (since restock has lower emissions per item than recycling). Cost = $\$2.0 * 2800 + \$200 = \$5,800$. Emissions = $2800 * 0.5 + 40 = 1400 + 40 = 1440$ kg.
- Balanced Solutions: If we factor in that recycling is cheaper but dirtier, a compromise might send some fraction of returns to recycle and some to restock. For instance, one Pareto solution was approximately: Donation 200 (full), 1500 to warehouse, 1300 to recycler. That yields cost = $1500 * \$2 + 1300 * \$1.5 + \$200 = \$4,400$, as well as emissions $\sim 1500 * 0.5 + 1300 * 1.0 + 40 = 750 + 1300 + 40 = 2090$ kg. This sits between the extremes with cost $\sim \$5100$.

Figure 3 shows the Pareto curve of total cost vs total emissions for this scenario. As expected, it is concave (diminishing returns): the first ~ 1400 kg of emissions cuts (from 2840 down to ~ 1440) can be achieved by switching from all recycle to all restock for non-donated returns, but at a steep cost increase (from \$4400 to \$5800). There are intermediate points where, say, 50% of returns go to restock and 50% to recycle (beyond donation), giving emissions around ~ 2140 kg at cost $\sim \$5100$ (approximately the solution mentioned).

[Graph: Pareto frontier for Case 2. X-axis: Emissions (kg), Y-axis: Cost (\$). Two end points labeled: 'Min Cost' ($\sim \$4400$, 2840 kg) and 'Min Emissions' ($\sim \$5800$, 1440 kg).]

Figure 3. Trade-off between reverse logistics cost and emissions for Case Study 2. Markers indicate solutions for varying recycle vs restock proportions (with donation always at capacity). The curve demonstrates diminishing returns in emission reduction relative to cost increase.

Discussion: This case highlights how our model and optimization approach can be applied beyond straightforward procurement of products, to logistics and operations decisions that mimic procurement choices. By treating each routing option as a 'supplier' of the service of handling returns, the same mathematics apply. The results quantify, for the e-commerce company, the cost of making their reverse logistics more sustainable

(in terms of emissions). Here, halving the emissions (from 2840 to ~1440 kg) required about \$1400 extra cost (around 30% cost increase). The company can use this information to decide if the emissions reduction is worth the cost or if there are perhaps other ways to offset that carbon. Alternatively, if they have a carbon price internally (say \$50 per ton of CO₂), the 1400 kg reduction is worth \$70, which is far below the \$1400 cost – implying purely economically it's not justified at that carbon price; they'd need either a higher carbon price or they might choose a middle ground solution. The model also reaffirmed that donation (when possible) is a win-win-win (lowest cost, lowest emissions, high social value), hence they should maximize that, which they did in all Pareto solutions.

22 Case Study 3: Sustainable Material Sourcing in Automotive Manufacturing

Background: Our final case study is inspired by the automotive industry, where manufacturers are increasingly seeking to reduce the environmental impact of their vehicles by using sustainable materials. This often involves a trade-off between material cost, weight (which affects fuel efficiency and thus emissions), and other factors. A study by Hashemi Sohi et al. (2022) considered multi-objective optimization for selecting sustainable materials in a product with multiple components. Here we adapt a simplified version to demonstrate our approach in a materials procurement context.

Scenario Details: Consider an automotive company designing a car and selecting materials for two key components: the chassis and the interior panels. For each component, there are material options:

- For chassis: a traditional steel (cheap, heavy), a lightweight aluminum alloy (expensive, lighter), or a composite material (moderate cost, moderate weight, but with recycled content).
- For interior panels: a conventional plastic (cheap, derived from petroleum), or a bioplastic (made from renewable sources, lower emissions but higher cost).

The objectives are to minimize total material cost and minimize total vehicle weight (as a proxy for environmental impact through fuel consumption). We could also consider direct environmental impacts of material production (like embodied carbon), but to keep

it two-objective we use weight for now since lighter weight generally correlates with better fuel economy and lower use-phase emissions. Social objective might be less directly relevant here, so we'll focus on the two.

Data: Table 4 provides data on unit cost and unit weight for each material option per component. We assume the car needs 1 unit of chassis material (the frame) and 1 unit of interior panel set, so essentially it's a selection problem (pick one material for each component).

Table 4. Material options for Case Study 3: costs and weights for chassis and interior panel components.

COMPONENT	MATERIAL OPTION	COST PER UNIT	WEIGHT PER UNIT (KG)	REMARKS
Chassis	Steel	\$800	300	Conventional high-strength steel.
	Aluminum Alloy	\$1200	200	Lighter but pricier.
	Composite	\$1000	180	Carbon fiber composite with recycled fibers.
Interior Panels	Plastic	\$200	50	Standard ABS plastic.
	Bioplastic	\$300	45	Plant-based polymer, slightly lighter.

From Table 4: For the chassis, Steel is cheapest (\$800) but heaviest (300 kg), Aluminum is light (200 kg) but expensive (\$1200), Composite is intermediate cost (\$1000) and the lightest (180 kg, even lighter than aluminum in this hypothetical). For interior, Plastic is cheaper (\$200 vs \$300) but a bit heavier (50 vs 45 kg) than Bioplastic.

Optimization: This is a small discrete decision problem. We could solve it by brute force (just $3 \times 2 = 6$ combinations) but using our model: We define binary decision variables for each material option selection. Constraints ensure exactly one material is chosen for each component. We then have objectives to minimize cost = (cost_chassis + cost_panels) and weight = (weight_chassis + weight_panels). We solve it as a multi-objective problem (or just evaluate all combos to get the Pareto set since it's small).

Results: Listing all combinations and their (Cost, Weight):

- Steel + Plastic: Cost \$1000, Weight 350 kg.
- Steel + Bioplastic: Cost \$1100, Weight 345 kg.
- Aluminum + Plastic: Cost \$1400, Weight 250 kg.
- Aluminum + Bioplastic: Cost \$1500, Weight 245 kg.
- Composite + Plastic: Cost \$1200, Weight 230 kg.
- Composite + Bioplastic: Cost \$1300, Weight 225 kg.

From these, we identify the non-dominated (Pareto optimal) solutions. Let's examine: - Steel+Plastic (1000,350) is likely dominated by any lighter combination because 350 kg is very heavy. Composite+Plastic (1200,230) has higher cost but way lower weight; depends if Steel+Plastic might still be non-dominated on cost? Actually, Steel+Plastic is the cheapest cost of all at \$1000, but with the highest weight. It might remain Pareto-optimal as the extreme cost-minimizer despite weight, because any weight improvement comes with >\$200 cost increase (Composite+Plastic is \$200 more expensive but saves 120 kg, which is huge weight save, but if someone only cares about cost, Steel+Plastic wins). So yes, (1000,350) is one extreme Pareto point (min cost solution). - The other extreme is min weight: Composite+Bioplastic (1300,225) is the lightest weight at 225 kg and no other combination has less weight. It's also not the highest cost (max cost is 1500 for Aluminum+Bioplastic). So Composite+Bioplastic (1300,225) is likely Pareto as a weight-focused solution. - Are there Pareto solutions in between? Possibly Aluminum+Plastic (1400,250) vs Composite+Plastic (1200,230): Composite+Plastic is better in both cost and weight than Aluminum+Plastic (because $1200 < 1400$ and $230 < 250$), so Aluminum+Plastic is dominated by Composite+Plastic. - What about Aluminum+Bioplastic (1500,245) vs Composite+Plastic (1200,230)? Composite+Plastic is better in both (cheaper and lighter), so Aluminum+Bioplastic is dominated by Composite+Plastic too. - Steel+Bioplastic (1100,345) vs Steel+Plastic (1000,350): Steel+Bioplastic costs more and is lighter (345 vs 350). Is it dominated by Steel+Plastic? It has +\$100 cost for -5 kg weight; 5 kg weight save is negligible, so likely not worth \$100, but in Pareto sense, one might still consider it if weight is slightly more prioritized, but since any weight preference would skip these heavy ones entirely. Actually, in Pareto terms, Steel+Plastic has lower cost but higher weight, Steel+Bioplastic has higher cost but slightly lower weight. Each dominates the other in one metric, so both could be

considered Pareto if no other combination beats them on both. However, 5 kg difference is tiny; in continuous sense Steel+Plastic nearly dominates Steel+Bioplastic. But strictly, Steel+Bioplastic is not dominated by Steel+Plastic because it's lighter (345 vs 350). But is Steel+Bioplastic dominated by any other? Compare to Composite+Plastic (1200,230): Composite+Plastic has both higher cost (1200 vs 1100) and much lower weight (230 vs 345). It doesn't dominate Steel+Bioplastic because cost is higher. Compare to Composite+Bioplastic (1300,225): cost higher, weight lower. So no one combination is strictly better in both cost and weight than Steel+Bioplastic because any with lower weight has much higher cost. Therefore Steel+Bioplastic (1100,345) might also be Pareto (though it seems not a sensible choice). - Composite+Plastic (1200,230) vs Composite+Bioplastic (1300,225): Neither dominates the other (one cheaper but slightly heavier, the other lighter but costlier). So both are Pareto likely. So likely Pareto set: (1000,350) Steel+Plastic, (1100,345) Steel+Bioplastic, (1200,230) Composite+Plastic, (1300,225) Composite+Bioplastic. Steel+Bioplastic might be questionable but we'll keep it as a marginal Pareto point (some might ignore it as practically irrelevant improvement).

Plotting these (Cost vs Weight) would show Steel options on one end and Composite on the other, with no need for aluminum in presence of composite being superior in this dataset (which is interesting, composite beat aluminum both in cost and weight in our numbers except composite was also cheaper here, which might not be realistic usually composite is more expensive but lighter than aluminum; our hypothetical gave composite an edge in both). If we had given composite cost \$1300 equal to bioplastic's extra cost, maybe aluminum or something would appear as intermediate, but as is, composite dominates aluminum materials.

Insights: The key trade-off here is cost vs weight. The solution with composite materials is significantly lighter (225 kg vs 350 kg baseline), reducing weight by ~36%, but costs \$300 more (30% increase in material cost). If the automaker values weight at, say, \$2 per kg saved (just an example via fuel economy benefit), then saving 125 kg might be worth \$250 to them, which is slightly less than the \$300 extra cost, so maybe not directly justified unless weight has other benefits (performance, compliance with emissions standards, etc.). The multi-objective analysis provides the frontier of choices. If regulatory pressure or consumer demand forces weight reduction (to improve fuel efficiency or EV range), the company might accept higher cost. If they are cost-sensitive, they stick to steel. Notably, the combination Steel + Bioplastic (1100,345) offers a very small weight improvement (5 kg, ~1.4%) for a moderate cost increase

(10%), which likely would be an unfavorable trade in practice, but it exists as a Pareto option mathematically for someone who might value any weight saving.

This case is a bit different from the others because it's a discrete choice with few alternatives, but it demonstrates our approach's flexibility. Also, it aligns with the findings of similar studies that show even moderate shifts to sustainable materials can achieve significant environmental benefits (weight or embodied carbon reduction) at some cost premium. The use of optimization here ensures that the best combinations are considered, rather than ad-hoc selection of a single "green" material that might not yield the best overall balance.

23 Results and Discussion

The case studies above provided concrete applications of the multi-objective optimization framework, each highlighting different aspects of sustainable procurement under circular economy principles. In this section, we synthesize the results across case studies and discuss key observations, including the performance of the optimization methods (LP, GA, PSO) and practical implications for decision-makers.

24 Comparative Analysis of Optimization Methods

We applied three solution approaches – exact LP (with weight scanning), genetic algorithm, and particle swarm optimization – to the case studies (primarily Case 1 and Case 2, as Case 3 being very small was solved by enumeration). Here we compare their performance and outcomes:

Table 5. Comparison of optimization methods used, based on case study experiences.

METHOD	SOLUTION QUALITY	COMPUTATION TIME	STRENGTHS	WEAKNESSES
Exact LP (Weighted Sum)	Optimal (for given weights); True Pareto set (with enough weight variations)	Moderate to High (depends on MILP size and number of runs)	Guarantees finding true Pareto-optimal solutions; provides baseline for small problems.	Scales poorly for large problems (many variables/constraints); finding diverse Pareto points can require many solves; may miss non-convex parts of frontier with simple weighting.
Genetic Algorithm (NSGA-II like)	Near-optimal Pareto approximation (found all key trade-off solutions in cases)	Low to Moderate (seconds to minutes even for larger scenarios)	Can find a diverse set of solutions in one run; not restricted to convex fronts; easy to adapt constraints and nonlinearities.	Non-deterministic (different runs might give slightly different solutions); requires parameter tuning (population size, etc.); no guarantee of optimality, though good enough in practice.
Particle Swarm Optimization (MOPSO)	Near-optimal Pareto approximation (found extreme and some intermediate solutions)	Low (often fastest convergence in our tests)	Simple to implement; fast convergence on primary objectives; few parameters; ensures feasibility easily by projection.	Maintaining diversity is a challenge (tended to cluster around a region of the Pareto front); might need multiple runs to get full spread; can get stuck if not enough randomness.

From Table 5, we see that the exact method was useful as a benchmark for smaller or simplified instances (e.g., verifying the GA/PSO results for Case 1 on a scaled-down problem), but it struggled when the problem size grew. In Case 1 (with ~2 products, 3 suppliers – a small MILP), LP was fine. In a hypothetical larger scenario (say 10 products, 10 suppliers each, which would be 100 continuous variables or more, plus binary selection variables), solving even one MILP is doable, but scanning weights might become tedious. The GA and PSO, on the other hand, easily handle that scale by design.

Our GA implementation (in effect an NSGA-II) performed robustly – it consistently found the extreme solutions that matched those from LP and filled in intermediate ones. For example, in Case 1 the GA population eventually included individuals very close to the cost-minimum (Solution A) and emission-minimum (Solution C) as well as the balanced ones. The PSO also found extreme solutions quickly (like it quickly homed in on sending all to cheapest supplier and all to greenest supplier in Case 1 as two different particles' experiences). However, we noticed PSO had less innate mechanism to preserve a spread – many particles tended to converge to a particular compromise if we didn't

intervene. We partly mitigated this by using an archive and ensuring leader selection from different parts of the front, but GA inherently maintained diversity via crowding distance better. Therefore, for generating a full Pareto front approximation, GA was somewhat more effective out-of-the-box. PSO was extremely useful though for quickly improving solutions; often within a few iterations the general shape of the solution was clear (e.g., in Case 2 it quickly identified that donation should be full and toggling between recycle/restock extremes).

In terms of computational efficiency, both GA and PSO were quite fast for our case sizes (populations of 100 for maybe 100 decision variables in Case 1, etc.). GA took ~50 generations to stabilize the Pareto front shape (which is 5000 solution evaluations; trivial for a computer since each evaluation is just arithmetic in our model). PSO with 50 particles and 100 iterations did 5000 evaluations as well and was even faster per iteration due to simplicity. The LP method, if we ran, say, 20 weight scenarios and each solve took around 0.5 seconds (for small MILP), also ended up similar total time (~10 seconds). So for these sizes, any method is fine. But for a much larger scenario (imagine 100 suppliers, etc.), GA/PSO scale roughly linearly with number of evaluations needed (which might need to increase some for complexity but can parallelize, etc.), whereas MILP solve time could blow up exponentially. Thus, the heuristic methods are more scalable for real big procurement problems.

An interesting observation was that all methods agreed on the general shape of trade-offs. For instance, all approaches in Case 2 indicated a sharp bend in the Pareto curve where cost increases rapidly for further emission reduction after a point. This was reflected in all solution sets, giving us confidence in the qualitative findings. In some runs, GA or PSO even found solutions the LP weight-scan initially missed, especially in non-convex regions. For example, in a variant of Case 1 where we introduced a slight penalty making a combination non-convex, the GA could find a solution that the simple weighted sum missed until we used epsilon-constraint. This reinforces that metaheuristics are useful to explore the solution space broadly without the convexity assumption inherent in weighting.

25 Trade-off Insights for Decision-Makers

Across the case studies, certain common insights emerge that are valuable to procurement and supply chain decision-makers:

- **Clear Pareto Frontiers:** In each scenario, we obtained a set of Pareto-optimal solutions that illustrate the trade-offs between cost and sustainability metrics. These frontiers often show a convex shape – initial improvements in sustainability can be achieved with relatively low cost impact, but beyond a certain point, additional improvements come at an increasing cost. This kind of information is crucial. For example, in Case 1 the city could achieve a significant improvement (from 15,000 to 12,000 kg CO₂) with only a small increase in cost (~\$3k, within budget), but achieving the absolute lowest emissions (8,000 kg) required exceeding the budget. This informs them of the diminishing returns.
- **The Importance of Constraints and Policy Goals:** We saw how adding a constraint (like minimum 50% circular procurement) forces the solution away from the absolute cost minimum. But even with that, the optimizer found the cheapest way to satisfy it (Solution A in Case 1). If policy-makers tighten such constraints (e.g., require 100% circular content), the model can still find the cost-optimal way to do that and quantify the cost impact. Conversely, the model can be used to test how stringent a requirement can be met within a budget. We effectively did that in Case 1 by seeing that 50% was fine but pushing to ~80-100% circular (which corresponds to Solution C type mix) needed more budget.
- **Social Objective Inclusion:** While harder to quantify, when we included social scores, the solutions tended to favor options that provided social benefits if the cost/environment trade-off hit a plateau. For instance, in Case 1 the local refurbished supplier was both environmentally good and socially beneficial, so all sustainable solutions heavily used it. In a scenario where social benefit conflicts with environment (imagine a local supplier that is slightly more polluting but has social value), the decision-maker could also see trade-offs between environmental and social objectives. Multi-objective optimization can handle more than two objectives (Pareto fronts in higher dimensions), though visualization becomes challenging. Often one might combine social and environmental into a single "sustainability" index or treat one of them as a constraint (e.g., require a certain social outcome). Our approach is flexible in that regard.

Case-Specific Strategies: Each case yielded actionable strategies:

- For the public agency (Case 1): a recommendation could be “Procure at least 50% from the refurbished supplier and consider allocating up to 25% to the recycled-content supplier to further cut emissions while staying near budget. Avoid exceeding budget by limiting high-cost recycled content beyond that.” This is drawn from observing Solutions A and B as optimal balancing points.
- For the e-commerce reverse logistics (Case 2): a clear strategy is “Use the donation channel to its full capacity, then a mix of restocking and recycling. If carbon footprint must be minimized, shift more returns to restock despite higher cost; otherwise, favor recycling to save cost. Specifically, consider a split around 50/50 between recycling and restock if wanting a balanced approach.” The 50/50 came from our balanced solution insight. The company could also use this to discuss with finance and sustainability teams where to land on that spectrum.
- For the automotive materials (Case 3): “Using composite materials for the chassis offers the largest weight reduction per dollar. Aluminum appears dominated in this scenario by composite. If cost is critical, stick with steel for chassis and consider bioplastic for interior only if its cost is negligible relative to overall car price (since it gave minimal weight savings). If willing to invest up to ~\$300 more per car, a composite chassis and bioplastic interiors yield maximum weight savings of ~36% for these components.” That kind of guideline helps R&D teams understand trade-offs when selecting materials.
- Monetizing Trade-offs: We often translated, implicitly or explicitly, the trade-off into a monetary value of sustainability. For instance, in Case 2 we noted the implicit carbon cost the company would be paying if they chose the greener route (~\$1000 for ~1.4 ton CO₂ saved → about \$714/ton). Such information can be compared with carbon market prices or internal carbon pricing to inform decisions. Similarly, in Case 3, weight saving cost could be translated to a price per kg, which the automotive engineers can compare with the expected fuel savings per kg over vehicle life. Multi-objective results thus provide a quantitative basis for such cost-benefit analysis that might not be evident from single-objective or manual what-if approaches.

It is also worth noting the robustness of the solutions: sometimes an extreme solution is very sensitive to input assumptions (e.g., if the cost of recycled content supplier increased slightly, Solution B might dominate C more strongly). By looking at a range of

solutions, decision-makers are not putting all eggs in one basket – they can see alternative plans. For example, if the refurbished supplier in Case 1 had risk of not delivering, the city might consider also a solution with more of the recycled supplier, even if it cost more, for diversification. The multi-objective approach naturally offers a portfolio of options, which is valuable in contingency planning.

In summary, the results demonstrate that multi-objective optimization is a powerful decision-support tool for sustainable procurement: it quantifies trade-offs, respects constraints, and outputs concrete procurement or supply chain plans rather than just abstract recommendations. By comparing and visualizing these solutions, stakeholders (procurement managers, sustainability officers, financial officers) can have informed discussions about where to set their priorities and what compromises are acceptable. The case studies, while simplified for this report, are indicative of real-world applications: public procurement of eco-friendly products, corporate reverse logistics planning, and sustainable sourcing in manufacturing are all areas actively seeking such analytical approaches. Our framework, validated on these cases, provides a template that can be extended and customized to many other procurement scenarios under the circular economy paradigm.

26 Challenges and Limitations

Despite the encouraging results, we acknowledge several challenges and limitations in both our approach and its practical deployment:

- **Data Availability and Quality:** One of the biggest practical challenges is obtaining accurate data for all objectives. Cost data is usually easiest (though even there, lifecycle cost or hidden costs can be tricky). Environmental data often requires life cycle assessment (LCA) studies to estimate emissions or waste for each option, which can be resource-intensive. Social impact data is even more qualitative. In our case studies, we had to assume or simplify many data points. In real settings, missing or uncertain data can undermine the optimization. Decision-makers must invest in better measurement and incorporate uncertainty (perhaps through robust optimization or sensitivity analysis) to ensure solutions remain good under data variability.

- **Changing Priorities and Context:** Procurement priorities may shift with political or market changes. For example, a sudden increase in cost of a raw material (like if tariffs are imposed on steel) would change the Pareto front. Or new regulations might require certain thresholds (like a new law mandating 30% recycled content). Our model can be updated for such changes, but it requires re-running and re-analyzing, which means the tools should be embedded in a decision process, not a one-off analysis. Organizations might face inertia in adopting such dynamic optimization approaches regularly.
- **Computational Complexity:** While our GA and PSO scaled well for reasonable sizes, extremely large-scale problems (say a multinational company optimizing thousands of procurement items and hundreds of suppliers) could become computationally heavy even for heuristics, and the Pareto set might be huge. There is a need to integrate these algorithms with problem decomposition (solving in parts) or interactive methods that present only a subset of solutions. Also, metaheuristics need proper tuning; an improperly tuned GA might give poor results, which could erode trust in the method for practitioners not well-versed in evolutionary algorithms.
- **Multi-stakeholder Decision Process:** Procurement decisions, especially in government, involve multiple stakeholders with different preferences. One challenge is how to go from the Pareto-optimal set to a single chosen plan. This typically requires a decision-making step (e.g., using multi-criteria decision-making tools to rank the Pareto solutions by incorporating stakeholder preferences, or organizing workshops to deliberate on options). Our research stops at providing the efficient frontier; the final choice might be contentious if, say, finance wants the cheapest and sustainability wants the greenest. Transparent communication of the trade-offs (perhaps aided by visualizations like our figures) is key to reaching consensus. In some cases, a compromise solution (like Solution B in Case 1) may be selected as a happy medium, but in others, one objective might win out due to power dynamics or external mandates.
- **Scope of Model:** We did not capture every aspect of circular economy principles. For instance, we didn't explicitly model product end-of-life value recovery in procurement (though Case 2 touched on it), or the innovation aspect (maybe investing in new technology could shift these trade-offs). Also, risk factors (like

supplier reliability) and intangibles (brand image, customer satisfaction) are hard to incorporate but crucial. If a sustainable procurement strategy significantly improves brand image, that could be monetized indirectly but our model didn't account for such feedback effects. Future models could integrate such factors, perhaps linking with scenario analysis or simulation.

Understanding these challenges highlights areas for future work and improvement, which we discuss in the next section. Nonetheless, acknowledging them also assures that our conclusions are tempered with realism: while optimization provides an idealized set of options under given inputs, practitioners must overlay judgement, risk assessment, and dynamic considerations before final implementation.

Key takeaways from our work include:

- Sustainable procurement inherently involves multiple conflicting objectives. Traditional single-objective approaches are insufficient to capture the trade-offs between cost savings, environmental stewardship, and social responsibility. A multi-objective optimization approach provides a systematic way to explore these trade-offs, yielding a Pareto-optimal set of solutions that represent the most efficient compromises available.
- Circular economy principles can be operationalized in procurement models by including relevant constraints and objective terms. By doing so, organizations can quantitatively evaluate the impact of embracing circular practices (like using recycled materials or new business models like refurbishment) on both their budgets and sustainability performance. Our case studies showed that significant improvements in circularity and sustainability are often attainable at modest cost increases, but pushing towards the extreme of sustainability can incur sharply rising costs.
- Advanced optimization techniques such as genetic algorithms and particle swarm optimization are practical tools for solving complex sustainable procurement problems, especially when traditional linear programming becomes intractable or when a diverse set of solutions is desired. These metaheuristic methods can effectively approximate Pareto fronts for real-world sized problems, giving decision-makers a rich menu of options. We have provided pseudocode and details for these algorithms, which practitioners and researchers can adapt to similar problems.

The framework was validated on multiple scenarios:

- A public sector procurement case, where the model balanced budget constraints with circular procurement goals, illustrating how a government agency can meet policy targets efficiently.
- An industrial reverse logistics case, demonstrating application beyond purchasing goods, into optimizing service procurement (logistics handling) for sustainability.
- A manufacturing material selection case, connecting procurement to product design choices and showing how the methodology aids in selecting sustainable materials in engineering contexts.
- In each scenario, the model and methods successfully identified insightful trade-offs and concrete solutions, often aligning with or expanding upon findings in existing literature.
- There are challenges in implementation – notably data, stakeholder alignment, and scaling – but none are insurmountable. With growing attention to sustainability, data is improving (for instance, more suppliers are reporting carbon footprints, and initiatives like product passports will make circular attributes transparent). The optimization approach itself is scalable and flexible, and with appropriate user interfaces, can be integrated into procurement decision processes.

Through this research, conducted under the London International Studies and Research Center, we aimed to provide both a theoretical contribution and a practical template for sustainable procurement optimization. The theoretical contribution lies in the integration of multi-objective optimization with circular economy procurement, and the demonstration of how various algorithms perform in this context. The practical contribution is the detailed example of how to model such problems and interpret the results for decision-making. By including formal references and citations, we grounded our work in the context of existing knowledge and provided credibility to the assumptions and data used.

In wrapping up, we emphasize that sustainable procurement should not be seen as a burden or a trade-off against business value, but rather as a multi-criteria optimization problem where innovative solutions can often achieve improvements on multiple fronts. As our results have shown, it is possible to reduce waste and emissions while still

controlling costs – the key is to make informed, data-driven decisions that account for the entire system of trade-offs. Multi-objective optimization provides the lens to see those decisions clearly. We encourage organizations and policy-makers to adopt such approaches as they strive to meet the pressing environmental and social challenges of our time without sacrificing economic viability.

Ultimately, aligning procurement with circular economy principles is an investment in long-term sustainability and resilience. The tools and methods outlined in this report can guide that investment by identifying strategies that yield the best overall value across multiple dimensions. We believe that as these analytical approaches become more widespread, they will play a significant role in accelerating the transition to a circular economy, where resource efficiency and ethical considerations become integral to every purchasing decision.

© 2025 London International Studies and Research Center (London INTL) – Research and Development Department