Journal of Cleaner Production 521 (2025) 146073

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Artificial intelligence-based optimization of the WEEE reverse chain in São Paulo – Brazil to promote economic, environmental and social benefits

Geraldo C.de Oliveira Neto [a,*], Rodrigo Neri Bueno da Silva [a], Gustavo Araújo Lima [b], Sidnei Alves de Araújo [b], Peterson Adriano Belan [b], Denilson Carvalho [c], Cecília M.V.B. Almeida [c]

[a] Industrial Engineering Post Graduation Program, Federal University of ABC, São Bernardo Do Campo, 09606-045, SP, Brazil
[b] Informatics and Knowledge Management Post-Graduation Program, Universidade Nove de Julho – UNINOVE, Rua Vergueiro 235/249, São Paulo, SP, Brazil
[c] Universidade Paulista, UNIP, R. Dr. Bacelar, 1.212, 4th Floor, 04026-002, São Paulo, SP, Brazil

ARTICLE INFO

Keywords:
Reverse logistic
WEEE
Optimization
Artificial intelligence
Environmental assessment
Economic assessment
Social benefits

ABSTRACT

The rapid growth in electronic production has intensified e-waste generation, underscoring the need for efficient Waste Electrical and Electronic Equipment (WEEE) reverse logistics systems coordinated by manufacturers, retailers, and public agencies. However, in some parts of the world, such as in São Paulo–Brazil, these systems still face substantial inefficiencies, resulting in increased environmental and social costs. This study focuses on applying artificial intelligence (AI) techniques to optimize the WEEE reverse logistics chain in São Paulo–Brazil, aiming to generate economic, environmental, and social benefits. The proposed approach integrates genetic algorithms, greedy local search and tabu search techniques, to reorganize recyclers, redistribute collection points, and enhance vehicle routing, thereby reducing travel distances, collection times, and environmental impacts. Data were collected from manufacturers, recyclers, and waste management companies to develop AI-based strategies that improve operational practices. Environmental impact was assessed using the Material Intensity Factor (MIF), revealing reductions in fuel consumption and greenhouse gas emissions, alongside societal benefits such as increased employment opportunities and improved occupational safety. The integration of AI with spatial data provides a practical tool for decision-makers, as evidenced by computational experiments showing approximately a 30 % reduction in travel distances and a 20 % decrease in collection times. These improvements lead to lower operational costs and significant environmental benefits, including the mitigation of over 4.5 million tons per year in combined impacts related to resource use, water consumption, and atmospheric emissions. These outcomes underscore the broader economic, environmental, and social benefits of WEEE management, fully aligned with the United Nations Sustainable Development Goals.

Acronyms

AI	Artificial Intelligence
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CPs	Collection Points
CPMP	Capacitated p-Median Problem
CVRP	Capacitated Vehicle Routing Problem
GA	Genetic Algorithm
GLS	Greedy Local Search
HC	Hydrocarbons
LCA	Life Cycle Assessment
MIC	Material Intensity per Compartment
MIF	Material Intensity Factor
NOx	Nitrogen Oxides
NSWP	National Solid Waste Policy
RECs	Recyclers
SDG	Sustainable Development Goals
TS	Tabu Search
UN	United Nations
WEEE	Waste Electrical and Electronic Equipment

* Corresponding author.
E-mail address: geraldo.prod@gmail.com (G.C.de Oliveira Neto).

https://doi.org/10.1016/j.jclepro.2025.146073
Received 30 December 2023; Received in revised form 24 June 2025; Accepted 28 June 2025
Available online 17 July 2025

1. Introduction

The rise in electronics manufacturing has led to a surge in waste electrical and electronic equipment (WEEE). Consequently, Brazilian law 12.305/2010 mandates the implementation of reverse logistics. Rogers et al. (1999) and Neto et al. (2018) highlighted that reverse logistics enables the reclamation of WEEE by reintegrating it into the production cycle and selling materials in the secondary market.

In 2019, a sectoral agreement was established among stakeholders in São Paulo's WEEE reverse chain, including manufacturers of electrical and electronic products, recyclers (RECs), waste management entities, and collection point (CP) operators. This initiative significantly strengthened the development of the reverse logistics system, with a clear emphasis on circularity (Oliveira Neto et al., 2023a). Active stakeholder participation is essential for achieving environmental benefits (Neto et al., 2021). The integration of reverse logistics with circular economy principles reveals a strong synergy, enhancing the value recovery potential of WEEE through collaborative engagement among chain participants (Llerena-Riascos et al., 2021; Guo and Zhong, 2023). Promoting material circularity supports practices such as reuse, recycling, and remanufacturing, while also reducing dependence on raw material extraction (Korhonen et al., 2018).

Within the sectoral agreement, electronics manufacturers decided to engage a WEEE manager responsible for executing reverse logistics using outsourced transportation. Their goal was to establish CPs and partnerships with RECs, all aimed at advancing the circularity of WEEE within São Paulo. This initiative targeted the reintroduction of materials into the production chain and subsequent resale in the secondary market (Oliveira Neto et al., 2023a). A primary ongoing challenge involves optimizing this reverse WEEE chain in São Paulo to ensure its capacity aligns with the market's demands. Consequently, the integration of artificial intelligence (AI) becomes crucial for route optimization (Oliveira Neto et al., 2023b), particularly in conjunction with IoT sensor utilization within the infrastructure (d Oliveira Neto et al., 2023a,b). This symbiosis facilitates the connection between AI and optimization processes to promote WEEE circularity, ultimately resulting in decreased environmental impacts (Garrido-Hidalgo et al., 2020).

Although several studies have investigated the optimization of waste collection systems, there is a lack of research integrating solutions aimed at reorganizing recyclers, redistributing collection points, and improving vehicle routing within a multi-objective framework supported by AI techniques, particularly in the context of WEEE management in developing countries. In this regard, no study has been identified that applies AI techniques to optimize the WEEE reverse logistics chain in São Paulo, Brazil, to generate economic, environmental, and social benefits. Thus, the research question of this study is: How can artificial intelligence be applied to optimize the WEEE reverse logistics chain in São Paulo, Brazil, to promote economic, environmental, and social benefits?

This study aims to apply AI techniques to optimize the WEEE reverse logistics chain in São Paulo, Brazil. The proposed approach involves strategic relocation of recycling centers (RECs), redistribution of collection points (CPs), and minimization of collection times and travel distances. To achieve this, a combination of Genetic Algorithm (GA), Greedy Local Search (GLS), and Tabu Search (TS) was employed. AI techniques are widely used across various fields, including optimization, classification, regression, clustering, time series analysis, and natural language processing. In the field of optimization, commonly used AI techniques include GA, TS, and GLS heuristics (Mantawy et al., 1999a, 1999b; Russell and Norvig, 2016). TS and GLS are based on concepts that intersect both AI and optimization fields (Pirim et al., 2008; Russell and Norvig, 2016; Mohamedyusf et al., 2024). GA, in particular, is widely recognized as a population-based algorithm with strong foundations in artificial intelligence (Gandomkar et al., 2005; Russell and Norvig, 2016; Ochelska-Mierzejewska et al., 2021).

Additionally, a crucial component was the adoption of the Material Intensity Factor (MIF) for environmental assessment, which involves factoring in the total volume of collected WEEE and evaluating pollutant gas emissions post-optimization.

The main contributions of this study are as follows:

(i) it integrates CPMP and CVRP into a unified optimization framework supported by AI techniques (GA, TS, and GLS);
(ii) it proposes a real-world application of this framework using data from São Paulo's WEEE reverse chain;
(iii) it employs the MIF methodology to assess environmental performance, explicitly considering energy consumption and emissions;
(iv) it explores economic, environmental, and social benefits, contributing to strategic decision-making aligned with circular economy principles;
(v) it highlights the study's alignment with the United Nations Sustainable Development Goals (UN SDGs), especially concerning environmental impact reduction and social inclusion.

The structure of this study comprises an introduction that outlines the research topic and highlights the specific gap being addressed. This is followed by sections covering the literature review, research methodology, results, discussion, and conclusion.

2. Literature review

A search string was formulated based on the set of keywords listed in Table 1. The search was conducted across the title, abstract, and keywords fields in the following databases: Scopus, Compendex, ScienceDirect, Emerald, Taylor & Francis, EBSCO, and Wiley Library. This search yielded 106 articles published in journals. During the content analysis process, articles addressing the optimization of WEEE transportation operations using mathematical modeling and AI, including heuristic and metaheuristic methods, were selected. Duplicate articles and studies dealing with recycling, reuse, disassembly line balancing, remanufacturing, and CPs capacity, but not addressing WEEE return transportation operations, were excluded. This resulted in forty-five articles that form the theoretical basis of the present study.

Table 2 presents forty-five papers, of which thirty-one adopted mathematical modeling to optimize WEEE reverse logistics transportation, while twelve employed AI-based approaches. In addition, two studies combined mathematical modeling with AI (mixed-integer linear programming with discrete event simulation or mixed-integer linear programming with GA).

From the studies employing mixed-integer linear programming, five were conducted in Turkey, focusing on WEEE reverse logistics optimization. Tari and Alumur (2014) examined locations and capacities of CPs, while Ayvaz et al. (2015) addressed demand uncertainties to maximize profits for third-party recyclers (RECs). Kilic et al. (2015) and Temur and Yanık (2017) designed cost-efficient networks incorporating RECs, CPs, and transportation. Bal and Satoglu (2018) proposed a multi-facility, multi-period optimization model for collection and transport. These studies support decisions related to facility selection, vehicle routing, and waste recovery, while contributing to CO_2 emissions reduction and job creation.

Achillas et al. (2010a, 2011) conducted two studies in Greece focused on reducing transportation costs for WEEE storage between collection points and recycling units. Their findings revealed transportation as the highest cost in reverse logistics, highlighting the importance of optimized facility locations and efficient intermediate storage infrastructure. In Colombia, Arias-Osorio et al. (2020) addressed vehicle location and routing challenges in WEEE collection, focusing on cost reduction, while Llerena-Riascos et al. (2021) proposed an optimization-based approach for designing sustainable WEEE management policies aligned with environmental standards. Similarly, Krikke (2011) optimized transportation and facility location configurations in

Table 1
Set of keywords and the search string used in the literature review.

Sets of keywords
"artificial intelligence", "optimization", "reverse logistics", "reverse chain", "closed loop", "collection centers", "collection points", "waste electrical", "WEEE", "Waste from Electrical and Electronic Equipment", "electronic waste", "e-waste"
Search string
(("artificial intelligence" or "optimization") AND ("reverse logistics" OR "reverse chain" OR "closed loop" OR "collection centers" OR "collection points") AND ("waste electrical" OR "WEEE" OR "Waste from Electrical and Electronic Equipment" OR "electronic waste" OR "e-waste"))

the closed-loop reverse chain of end-of-life copiers in the Netherlands, aiming to minimize the carbon footprint.

Many studies have examined different aspects of WEEE reverse logistics optimization across various countries. Gomes et al. (2011) examined the optimal locations for collection and sorting centers in Portugal, while Alumur et al. (2012) focused on profit maximization in reverse logistics network design in Germany. Assavapokee and Wongthatsanekorn (2012) investigated efficient selection methods for implementing recycling units in Texas, USA, achieving a reduction in CO_2 emissions. Elia et al. (2019) compared WEEE collection alternatives in Italy, identifying the most effective solutions for minimizing emissions. Qiang and Zhou (2016) optimized the reverse logistics network in China, contributing to greater efficiency in WEEE management systems.

Safdar et al. (2020) employed mixed-integer linear programming to optimize WEEE management in Pakistan, focusing on collection centers, distribution hubs, and transportation to maximize profit, reduce carbon emissions, and enhance employment opportunities. Their findings indicated that transportation was the most significant cost driver, with both reprocessing and transportation identified as the main sources of carbon emissions. Allehashemi et al. (2022) optimized a cell phone reverse logistics chain in Ontario, Canada, concluding that closer facility proximity significantly reduces both costs and emissions. Harijani et al. (2023) developed a closed-loop WEEE reverse chain in Iran, integrating sustainability and budget constraints into recycling implementation; their mathematical model minimized costs while enabling payment of carbon emission taxes. Kannan et al. (2023) designed a multi-product WEEE reverse chain in India, incorporating diverse recovery facilities, processing technologies, and vehicle types, successfully lowering costs and emissions while supporting improvements in regulatory policies.

Several studies have employed multicriteria objective linear programming to optimize WEEE reverse logistics networks, focusing on both environmental and economic goals. Two studies conducted in Greece pinpointed optimal locations for waste recycling plants to minimize CO_2 emissions (Achillas et al., 2010b) and enhanced WEEE collection and recycling processes to decrease logistics costs, fuel consumption, emissions, and landfill disposal (Achillas et al., 2012). Quariguasi Frota Neto et al. (2010) examined the environmental impacts of the Dutch reverse network and concluded that WEEE reverse chains are sustainable, as they lower CO_2 emissions and prevent improper waste disposal. Mar-Ortiz et al. (2011) developed Spain's logistics network with an economic emphasis, while Yu and Solvang (2016) tackled uncertainties in China's reverse logistics system, aiming to reduce CO2 emissions. Da Silva Sales et al. (2023) investigated the feasibility of WEEE pre-treatment units in Brazil, discovering that smaller units and shorter transportation distances were cost-effective, with two or more pre-treatment units providing greater efficiency.

Gamberini et al. (2010) and Shokohyar and Mansour (2013) used discrete event simulation to optimize WEEE transportation networks in Italy and Iran, respectively, with a focus on CO_2 reduction. In China, Dat et al. (2012) applied linear and nonlinear optimization to minimize recycling network costs, while Guo and Zhong (2023) developed a closed-loop supply chain using the Internet of Things, addressing CO_2 emissions and occupational safety. Lv and Du (2021) employed a kriging-based mathematical model to forecast WEEE returns, enhancing environmental compliance. Bruno et al. (2021) introduced quantitative indicators to assess CP accessibility across Italian regions, supporting decisions related to CP placement, cost optimization, and environmental compliance in WEEE reverse logistics.

Numerous studies have applied AI techniques, including heuristic and metaheuristic methods, to optimize WEEE reverse logistics, five of which employed multi-objective and fuzzy models. In China, Liao and Luo (2022) developed a fuzzy optimization model for facility location selection, reducing CO_2 emissions from electric vehicle battery recycling while improving performance, profitability, and decision-making. Hou et al. (2023) optimized low-carbon WEEE collection schedules by considering stakeholder conflicts, road congestion, and emissions, while Wang et al. (2023) improved reverse chain operations for electric vehicle batteries, achieving cost reductions and regulatory compliance. Tosarkani et al. (2020) employed fuzzy models in Canada to prevent WEEE from ending up in landfills, ensuring CO_2 reductions and regulatory alignment. Najm and Asadi-Gangraj (2024) designed a WEEE network in Iran aimed at cost optimization, workplace safety, job creation, and environmental improvement.

Some studies have applied Genetic Algorithms (GA), including Oliveira Neto et al. (2023a,b), who optimized WEEE collection routes in São Paulo, Brazil, resulting in reduced fuel and lubricant consumption. Similarly, Ruan et al. (2021) focused on minimizing costs and CO_2 emissions in Pernambuco, Brazil, supporting policymakers in CP location decisions. Collectively, these studies highlight the role of AI in streamlining WEEE logistics while balancing economic, social, and environmental objectives.

Duman et al. (2019) and Zhang et al. (2022) employed convolutional neural network-based approaches for WEEE management. The former developed a predictive model in the United States to reduce CO_2 emissions, while the latter designed a closed-loop system for random WEEE capture in Belgium. In France, Habibi et al. (2017) applied a two-phase iterative heuristic algorithm to optimize reverse logistics costs, achieving efficient solutions with low computational times to coordinate end-of-life product collection at dismantling centers. Moslehi et al. (2021) combined mixed-integer linear programming and discrete event simulation to address uncertainties in WEEE reverse logistics, focusing on CO_2 reduction and landfill diversion. Similarly, Chen et al. (2024) integrated mixed-integer linear programming with Genetic Algorithms to maximize profit, reduce emissions, and enhance circularity in cell phone recycling. Their model not only balanced profit and emissions reduction but also raised environmental awareness among consumers and helped mitigate collection costs during market maturity stages.

Only a few studies in the literature have explicitly reported social outcomes resulting from the optimization of WEEE reverse logistics. Four studies highlighted employment generation aimed at reducing informal operations in Turkey (Bal and Satoglu, 2018), Iran (Shokohyar and Mansour, 2013; Najm and Asadi-Gangraj, 2024), and Pakistan (Safdar et al., 2020). Local development through WEEE reverse logistics was also explored in China—focused on monetizing carbon credits (Chen et al., 2024)—and in Iran, where economic challenges such as inflation and unemployment prevail. Improvements in workplace safety in recycling and transportation were noted in Singapore (Guo and Zhong, 2023) and Iran (Najm and Asadi-Gangraj, 2024). Shokouhyar and Aalirezaei (2017) additionally observed cost and CO_2 reductions, job creation, and local development. These findings underscore how low-income countries can leverage WEEE reverse chains to promote employment, occupational safety, and development, while nations like

Table 2
Works addressing mathematical modeling and AI for WEEE reverse chain optimization (Achillas et al., 2010a; Achillas et al., 2011; Krikke, 2011; Gomes et al., 2011; Alumur et al., 2012; Assavapokee and Wongthatsanekorn, 2012; Tari and Alumur, 2014; Ayvaz et al., 2015; Kilic et al., 2015; Qiang and Zhou, 2016; Temur and Yanık, 2017; Bal e Satoglu, 2018; Elia et al., 2019; Safdar et al., 2020; Arias-Osorio et al., 2020; Llerena-Riascos et al., 2021; Allehashemi et al., 2022; Harijani et al., 2023; Kannan et al., 2023; Quariguasi Frota Neto et al., 2010; Mar-Ortiz et al., 2011; Achillas et al., 2010b; Achillas et al., 2012; da Silva Sales et al., 2023; Yu and Solvang, 2016; Gamberini et al., 2010; Shokohyar and Mansour, 2013; Dat et al., 2012; Guo and Zhong, 2023; Lv and Du, 2021; Bruno et al., 2021; Tosarkani et al., 2020; Liao and Luo, 2022; Wang et al., 2023; Najm and Asadi-Gangraj, 2024; Hou et al., 2023; Shokouhyar and Aalirezaei, 2017; Li and Lu, 2021; Ruan Barbosa de Aquino et al., 2021; Oliveira Neto et al., 2023; Duman et al., 2019; Zhang et al., 2022; Habibi et al., 2017; Moslehi et al., 2021; Chen et al., 2024).

Author/Year	Mathematical Modeling						Artificial Intelligence					Economic Benefits	Enviromental Benefits				Social Benefits		
	Mixed-integer linear programming	Multicriteria objective linear programming	Discrete Event Simulation	Linear and nonlinear optimization methods with discrete and continuou variables	Kriging methods	Quantitative indicators	Multi-objective models	Genetic Algorithm	Other Heuristic and Metaheuristic Methods	Convolutional Neural Networks	Circular Economy	Reduced transport costs	CO2 reduction	Environmental compliance	Elimination of WEEE disposal in landfills	Minimization of lubricants and diesel oil	Safety at work	job creation	Local development
Achillas et al., (2010a)	×											×							
Achillas et al., (2011)	×											×							
Krikke (2011)	×												×						
Gomes et al. (2011)	×											×							
Alumur et al. (2012)	×											×							
Assavapokee and Wongthatsanekorn (2012)	×											×	×						
Tari and Alumur (2014)	×											×							
Ayvaz et al. (2015)	×											×							
Kilic et al. (2015)	×											×							
Qiang and Zhou (2016)	×											×							
Temur and Yanık (2017)	×											×							
Bal e Satoglu (2018)	×											×	×					×	
Elia et al. (2019)	×											×	×						
Safdar et al. (2020)	×											×	×					×	
Arias-Osorio et al (2020)	×											×							
Llerena-Riascos et al. (2021)	×										×	×		×					
Allehashemi et al. (2022)	×											×	×						
Harijani et al. (2023)	×											×	×	×					
Kannan et al. (2023)	×											×	×	×					
Frota Neto et al. (2010)		×											×		×				
Achillas et al., (2010b)		×										×	×		×				
Mar-Ortiz et al. (2011)		×										×							
Achillas et al., (2012)		×										×	×						
Yu and Solvang (2016)		×										×	×						
da Silva Sales et al. (2023)		×										×							
Gamberini et al. (2010)			×									×	×						
Shokohyar and Mansour (2013)			×									×	×					×	×
Dat et al. (2012)				×								×							
Guo and Zhong (2023)				×							×	×	×				×		
Lv and Du (2021)					×									×					
Bruno et al. (2021)						×					×	×		×					
Tosarkani et al. (2020)							×				×	×	×	×	×				
Wenzhu Liao and Luo (2022)							×				×	×	×						
Wang et al. (2023)							×					×	×	×					
Hou et al. (2023)							×						×						
Najm and Asadi-Gangraj (2024)							×					×	×		×		×	×	×
Shokouhyar and Aalirezaei (2017)								×				×	×		×		×	×	×
Li and Lu (2021)								×				×							
Ruan et al. (2021)								×				×	×	×					
Oliveira Neto et al. (2023)								×				×	×			×			
Duman et al. (2019)										×			×						
Zhang et al. (2022)										×		×							
Habibi et al. (2017)									×			×							
Moslehi et al. (2021)	×		×									×	×		×				
Chen et al. (2024)	×							×			×	×	×						×
Our Work								×	×		×	×	×	×	×	×	×	×	×

China can drive growth through carbon credit strategies, highlighting research opportunities aligned with the UN SDGs.

Most of the reviewed works focus on specific objectives, such as facility location (e.g., Liao and Luo, 2022), route optimization (e.g., Hou et al., 2023), emission reduction (e.g., Tosarkani et al., 2020), cost minimization (e.g., Chen et al., 2024), or the reduction of fuel and lubricant consumption (e.g., Oliveira Neto et al., 2023a,b). Despite the methodological diversity in terms of techniques employed, the application of AI in WEEE management reflects a growing interest in leveraging advanced computational tools to support sustainability-oriented decision-making. However, the review also highlights key limitations that remain unaddressed. Few studies simultaneously integrate strategically locating RECs closer to CPs and vehicle routing within a unified AI-based optimization framework. Moreover, the joint resolution of CPMP and CVRP models using AI techniques is rarely explored, particularly in operational contexts of developing countries. Environmental assessments often remain restricted to CO_2 emissions, overlooking more comprehensive indicators. Additionally, social benefits—such as job creation and improvements in occupational safety—are either scarcely addressed or entirely absent.

The present study addresses these challenges by applying AI-based techniques to optimize the WEEE reverse logistics chain in São Paulo. In doing so, it achieves operational improvements and environmental benefits, while advancing the field through innovative optimization strategies. The proposed model also incorporates environmental assessment using the MIF (de Oliveira Neto and de Sousa, 2014) and considers social implications aligned with the UN SDGs, thereby offering an integrated and scalable approach to WEEE reverse logistics optimization.

3. Research methodology

The methodology encompasses comprehensive details on data collection procedures and analysis.

3.1. Data collection, considering analysis with experts via interviews

Interviews were conducted with managers from four electrical and electronic product manufacturers, the contracted WEEE management company responsible for operations, and three RECs, all based in São Paulo. These semi-structured interviews aimed to gather data from experts within companies involved in the reverse WEEE chain. The data collected focused on the locations of key players (CPs and RECs) as well as the volume and types of WEEE processed. Bogner et al. (2009) emphasized the importance of expert analysis through semi-structured interviews in gathering accurate data that is crucial for developing research with both theoretical and practical contributions.

3.2. Data analysis

The data, including player locations (CPs and RECs) and the volume and types of WEEE processed, were compiled into a spreadsheet. These data served as input variables for applying GA and GLS techniques to solve the problems of relocating RECs and redistributing CPs, and for using the TS algorithm to optimize the routing of vehicles used in collections. This approach facilitated the analysis aimed at environmentally optimizing São Paulo's WEEE reverse chain.

To measure environmental benefits, the MIF was incorporated, considering the total volume of WEEE collected and the emissions of polluting gases after optimizing the routing for collections. The use of the MIF instead other methodologies such as Life Cycle Assessment (LCA) is fully justified, as it provides a practical and scientifically recognized approach for assessing the environmental aspects of reverse logistics systems, particularly in operational contexts with data limitations and decision-making constraints, such as the management of WEEE collection in São Paulo. Widely adopted in the literature, MIF enables a consistent evaluation of material flows, including energy consumption and associated emissions, which are explicitly considered in this study, as shown in Tables 3 and 7. Given its applicability and robustness, MIF represents a suitable methodological choice aligned with the scope and objectives of this research.

The data analysis procedure involved describing and formulating the addressed problems, proposing an approach for optimization of WEEE transportation, geolocating the data, developing optimization solutions, spatializing the data, summarizing and analyzing economic results, establishing procedures for environmental assessment, and analyzing social implications resulting from the optimization.

3.2.1. Addressed problems: description and formulation

This research addresses the challenge involving three RECs responsible for collecting WEEE across 554 CPs scattered throughout São Paulo state. Considering the current situation where long travel distances are often necessary for collections, leading to negative economic and environmental effects, the proposed approach aims to improve the WEEE reverse logistics chain. It suggests establishing new REC locations, reallocating CPs to be served by the RECs while considering their capacities, and optimizing the routing of vehicles involved in WEEE collection.

The task of reallocating the three RECs and assigning which CPs will be served by each REC can be formulated as a single problem commonly referred to in the literature as the capacitated p-median problem (CPMP). This problem entails localizing facilities within a network of n vertices (customers) and determining which facility will serve each vertex. The objective is to minimize the total distance between customers and the facilities that will serve them while adhering to the maximum capacity constraints of each facility (Garey and Johnson, 1979; Ghoseiri and Ghannadpour, 2007; Oksuz et al., 2023).

In our CPMP model, facilities represent the RECs, and customers represent the CPs. In addition, we consider each CP location to be a candidate site for a REC. However, even if they share the same geographic location, the CP and the REC are distinct entities, i.e., CP is not converted into REC. In this circumstance, we have 554 candidate sites for the installation of the three RECs.

Let I *e* J the set of CPs and the set of candidate locations for installing RECs, respectively, with $|I| = |J| = 554$; $K = \{1, 2, 3\}$ the set of RECs to be installed with predefined capacities; d_{ij} is the distance between CP $i \in I$ and candidate location $j \in J$; w_i the amount of waste generated by CP i; Q_k the capacity of REC $k \in K$; z_{jk} indicates REC k installed at location j; y_{ijk} indicates CP i assigned to REC k installed at location j. Then, the CPMP can be mathematically modeled by equations (1)–(9), as follows:

$$Min \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} d_{ij} y_{ijk} \tag{1}$$

$$\text{Subject to}: \sum_{j \in J} \sum_{k \in K} y_{ijk} = 1; \ \forall i \in I \tag{2}$$

$$y_{ijk} \le z_{jk}; \quad \forall i \in I, \forall j \in J, \forall k \in K \tag{3}$$

$$\sum_{j \in J} z_{jk} = 1; \ \forall k \in K \tag{4}$$

$$\sum_{k \in K} z_{jk} \le 1; \ \forall j \in J \tag{5}$$

$$\sum_{i \in I} w_i \cdot y_{ijk} \le Q_k; \ \forall j \in J, \forall k \in K \tag{6}$$

$$z_{jk}, y_{ijk} \in \{0, 1\}; \ \forall i \in I, \forall j \in J, \forall k \in K \tag{7}$$

The constraints (2) to (6) ensure that: each CP must be assigned to exactly one REC (2); assignment is only allowed if the corresponding REC is installed (3); each REC must be installed at exactly one location

(4); at most one REC per location (5); capacity constraint for each installed REC (6). Finally, constraint (7) maintain the condition of completeness, where:

$$z_{jk} = \begin{cases} 1, \text{if REC } k \text{ is installed at location } j \\ 0, \mathit{otherwise} \end{cases} \tag{8}$$

$$y_{ijk} = \begin{cases} 1, \text{if CP } i \text{ is assigned to REC } k \text{ installed at location } j \\ 0, \mathit{otherwise} \end{cases} \tag{9}$$

Considering that the groups (clusters) of CPs to be served by the RECs have been defined, the final step in optimizing the WEEE reverse logistics chain involves vehicle routing. This task is modeled as the well-known Capacitated Vehicle Routing Problem (CVRP). In our study, the CVRP consists of determining a set of routes for WEEE collection within each cluster to minimize the total distance traveled, while satisfying the following constraints: i) each route must start and end at the same REC (depot); ii) on each route a CP must be visited only once; and iii) the sum of waste generated by CPs belonging to a route cannot exceed the vehicle capacity.

Let I_k the set of CPs assigned to REC k; $V_k = I_k \cup \{0\}$ the set of all nodes in cluster k, where node 0 is the REC (depot); E_k the set of edges connecting all nodes in V_k; d_{ij} the distance between nodes i and j; w_i the waste generated by CP i; C the vehicle capacity; x_{ij} indicates vehicle travel from node i to node j; $u_i \in \Re$ indicates load of the vehicle upon arriving at node i, used for subtour elimination. Then, the CVRP can be mathematically formulated by equations (10)–(17), as follows:

$$Min \sum_{i \in Vk} \sum_{j \in Vk, j \neq i} d_{ij} x_{ij} \tag{10}$$

$$\text{Subject to}: \sum_{j \in Vk, j \neq i} x_{ij} = 1; \ \forall\, i \in Ik \tag{11}$$

$$\sum_{j \in Vk, j \neq i} x_{ji} = 1; \ \forall\, i \in Ik \tag{12}$$

$$u_i - u_j + C \cdot x_{ij} \leq C - w_j; \ \forall\, i \neq j \in Ik \tag{13}$$

$$w_i \leq u_i \leq C; \ \ \forall\, i \in Ik \tag{14}$$

$$\sum_{j \in Ik} x_{0j} = r_k \tag{15}$$

$$\sum_{i \in Ik} x_{i0} = r_k \tag{16}$$

$$x_{ij} \in \{0, 1\}; \ \ \forall\, i, j \in V_k, i \neq j \tag{17}$$

Constraints 11 and 12 specify that each CP is visited exactly once, while constraints 13 and 14 enforce that no single route exceeds vehicle capacity, which naturally allows the model to create multiple feasible routes if needed. Constraints 15 and 16 ensure that each route must start and end at REC k, where r_k is the number of vehicles used for REC k, implicitly determined by demand and vehicle capacity. Finally, equation (17) only makes it clear that the variable x_{ij} is binary.

It is important to highlight that: i) the mathematical formulations of the two problems (CPMP and CVRP) are not new, but have been adapted to the specific context of WEEE reverse logistics in São Paulo; ii) the two problems are solved sequentially. This decision was made to ensure better control over the individual objectives of each phase: the CPMP determines the optimal locations of RECs and allocation of CPs, while the CVRP minimizes routing distances based on the CPMP output. A sequential solution was also preferred due to the large scale and complexity of the dataset, which would significantly increase computational demands if both problems were solved simultaneously.

3.2.2. Optimization of WEEE reverse logistics

The approach proposed in this study addresses both the CPMP and CVRP, directly contributing to the reduction of economic costs, which in turn support the achievement of environmental benefits and social impacts associated with the WEEE reverse logistics chain. Economic costs are estimated based on the distances traveled during collection, while ensuring that the waste volume assigned to each recycler does not exceed its processing capacity. As shown in Fig. 1, the optimization approach involves a sequence of four interconnected computational procedures, detailed in Subsections 3.2.3 to 3.2.6. All algorithms implemented in these procedures were developed using the Python language.

The integration of AI techniques, including GA and GLS for addressing the CPMP, and TS for tackling the CVRP, alongside spatial data tools, marks a substantial leap forward in optimizing waste collection systems, allowing the achievement of economic, environmental, and social benefits.

GA is an evolutionary AI technique for optimization, inspired by natural selection and genetics. It iteratively evolves a population of potential solutions to a problem using selection, crossover, and mutation operators. Best individuals are selected based on a fitness function, and their genetic material is combined to create offspring through crossover. The diversity of population is achieved by the mutation operation. This process continues over multiple generations until a stopping criterion is reached (Goldberg, 1989; Russell and Norvig, 2016; Lima and Araújo, 2018; Ochelska-Mierzejewska et al., 2021). GLS is based on the well-known Hill Climbing heuristic to iteratively improve the current solution by moving to neighboring solutions that have a better objective function value (Russell and Norvig, 2016; da Silva Lourenço et al., 2018). TS is a local search algorithm that explores the solution space iteratively, making incremental changes to the current solution while avoiding revisiting recently explored solutions recorded in a short-term memory, known as the "tabu list," which prevents the algorithm from getting trapped in local optima (Gandomkar et al., 2005; Pirim et al.,

Table 3
Material intensity factors (MIF).

Description	Material intensity units [t/t]			
	Abiotic (w)	Biotic (x)	Water (y)	Air (z)
ABS Plastic	3.97		206.89	3.75
Iron	21.58		504.86	5.07
Glass	2.95		11.65	0.74
Copper	348.47		367.16	1.6
Styrene/butadiene	5.7		146	1.65
Ferrite (molybdenum)	748		1286	9.5
Stainless steel	9.42		75.38	0.65
Low-alloy steel (recycled)	1.47		58.76	0.52
Silver	7.5		0	0
Gold	540		0	0
Palladium	320.301		192.728	13772
Common aluminum	18.98		539.21	5.91
Nickel	141.29		233.34	40.83
Lead	18.12		135.8	2.28
Tin	8.486		10958	149
Zinc	23.1		0	0
Polypropylene	2.09		35.8	1.48
Polycarbonates	6.94		212.19	4.7
PVC	3.47		305.29	1.7
Pottery	2.11		5.74	0.05
Fiberglass (resistive)	10.84		296.25	2.01
Diesel oil	1.36		9.7	0.02
Engine Oil	1.5		11.45	3.02
Coolant Fluid (Ethylene Glycol)	2.9		133.46	2.29
Water	0.01		1.3	0
	Material intensity units [t/kWh]			
Electricity	3.15	0.04	57.64	0.51

2008; Russell and Norvig, 2016; Mohamedyusf et al., 2024).

3.2.3. Geolocation of data

In this procedure, latitude and longitude coordinates are gathered from CPs and RECs across São Paulo, Brazil. This step is crucial for spatially organizing data on maps. Additionally, the geolocations of both RECs and CPs serve as the basis for computing distance and time matrices. These matrices aid in determining the distances and overall time taken for vehicle routes during waste collection and are employed to solve CPMP and CVRP. Geolocating the points was accomplished using the Open Source Routing Machine library.[1]

3.2.4. Solving CPMP and CVRP

The CPMP solution combines a Genetic Algorithm (GA) with a Greedy Local Search (GLS) algorithm (Appendix 1), the latter applied exclusively to generate the initial GA population, ensuring that the solutions are feasible and respects all capacity constraints. The high-quality starting solutions provided by GLS, combined with the GA's ability to explore multiple solutions in parallel, help accelerate convergence and enable the identification of optimal or near-optimal solutions within a computationally feasible timeframe (Lima and Araújo, 2018; de Araujo Lima et al., 2018; Ochelska-Mierzejewska et al., 2021).

Each GA chromosome consists of 557 genes encoded as integers. The first three genes represent the selected RECs, chosen from a list of candidate locations. The remaining 554 genes correspond to an ordered permutation of the CPs (numbered from 1 to 554), which defines the sequence in which they should be assigned to the three RECs.

To compose each solution of the initial population, GLS assigns each CP to the nearest REC with enough remaining capacity. Ties are resolved by choosing the REC with the highest residual capacity. For each solution, the locations of the three RECs are chosen randomly.

The following steps are performed to decode a chromosome into a CPMP solution: 1. The three REC locations are activated based on the first three genes; 2. Starting from the first REC, CPs are assigned sequentially (following the order defined by genes 4 to 557); 3. For each CP, the waste amount is added to the current REC's load; 4. When the REC reaches its capacity (or proportion), the assignment process continues with the next REC; 5. This continues until all CPs are assigned. If needed, the decoding procedure incorporates pre-defined proportions to guide the expected load distribution across the RECs.

The GA was configured with a population size of 50 individuals and executed over 100 generations. Crossover was applied with a probability of 0.7 using the uniform crossover operator, while mutation was applied with a probability of 0.2 using the shuffle index mutation. Tournament selection with size 3 was used to choose individuals for reproduction. The fitness function implements the objective function of the CPMP (Equation (1)), penalizing infeasible solutions that violate the constraints defined in Equations (2)–(6), and assigning lower fitness values to solutions that achieve shorter total distances between CPs and RECs.

Once the locations of the three RECs and the corresponding sets of assigned CPs are defined, the next step consists in computing vehicle routes for each REC, that is, solving CVRP. This is accomplished using the Tabu Search (TS) algorithm, as detailed in Appendix 2. It's important to note that the TS algorithm's parameterization follows the standard settings defined within the OR-Tools library,[2] which was employed in the computational experiments performed. The evaluation of the solutions generated by TS is based on equations (10)–(16) presented in Section 3.2.1.

The TS algorithm distinguishes itself through its capability to evade local minima, facilitating a more extensive exploration of the solution space. The inclusion of a "tabu list," which prevents re-evaluation of recently explored solutions, effectively prevents repetitive cycles and steers optimization towards uncharted areas. This attribute holds significant value in intricate problems like CVRP, where the range of potential solutions is very extensive.

3.2.5. Spatialization of data

In this procedure, the outcomes obtained from the CPMP and CVRP solutions—namely, REC locations, CP groupings, and routes—are visually displayed on maps accessible via a web page. As illustrated in Fig. 2, each color represents a cluster of CPs assigned to a specific REC. This process involves the use of OpenStreetMap,[3] combined with the Open Source Routing Machine and the folium[4] library. It is important to highlight that while the Google Maps[5] platform is more prevalent in everyday use, its accessibility often requires service contracts through its application programming interface or may have usage limitations under free-use conditions. Therefore, the integration of Open Source Routing Machine with folium and OpenStreetMap serves as a significant free and open substitute for Google Maps in both distance computations and spatial data visualization.

3.2.6. Summarizing and analyzing the results

The fourth procedure encompasses summarizing and analyzing the generated results, including aggregating the total distance covered and time expended for the collections carried out by each REC. An additional visualization option involves individual route analysis for each vehicle, enabling advance planning of travel distance and expected completion times. However, it is essential to note that these values are estimations and do not account for real-time factors like accidents, traffic, or other potential interferences along the route.

In addition to quantitatively evaluating the optimized collection network's performance, the summarized data facilitates calculating the reduction of economic costs and environmental impacts resulting from the presented procedures. Moreover, with all results computed, there's an opportunity to integrate the RECs' activities with the social aspects outlined in Section 3.3, potentially generating collective societal benefits.

3.2.7. Procedure for economic and environmental assessment

A focused economic evaluation was conducted to estimate the costs associated with relocating a company's headquarters to a different city within the same state, as well as the potential savings resulting from altering transportation routes. The complete procedure is available in Appendix 3. The MIF tool was used to assess the environmental impact, determining whether the outcome was positive or negative. The mass balance was constructed considering the collected volume of WEEE, as well as the consumption of fuel and lubricants in the vehicles before and after optimization. The MIF is calculated by multiplying the mass of the residue (M) by the intensity factor (IF), as shown in Equation (18).

$$MIF = (M \times IF) \tag{18}$$

Through the utilization of the MIF, we were able to assess the environmental impact across biotic and abiotic compartments, including land and air. Biotic compartments involve living organisms, such as plants and decomposers, while abiotic compartments comprise non-living ecosystem factors, like pressure, temperature, and rainfall, as detailed in Table 3.

To gauge the reduction in environmental impact, we multiply the factor of each abiotic (w), biotic (x), water (y), and atmospheric (z) compartment by the reused or recycled mass. This computation yields the material intensity per compartment (MIC), as outlined in Equation (19).

[1] https://project-osrm.org.
[2] https://developers.google.com/optimization?hl=pt-br.
[3] https://www.openstreetmap.org/.
[4] https://pypi.org/project/folium/.
[5] https://maps.google.com/.

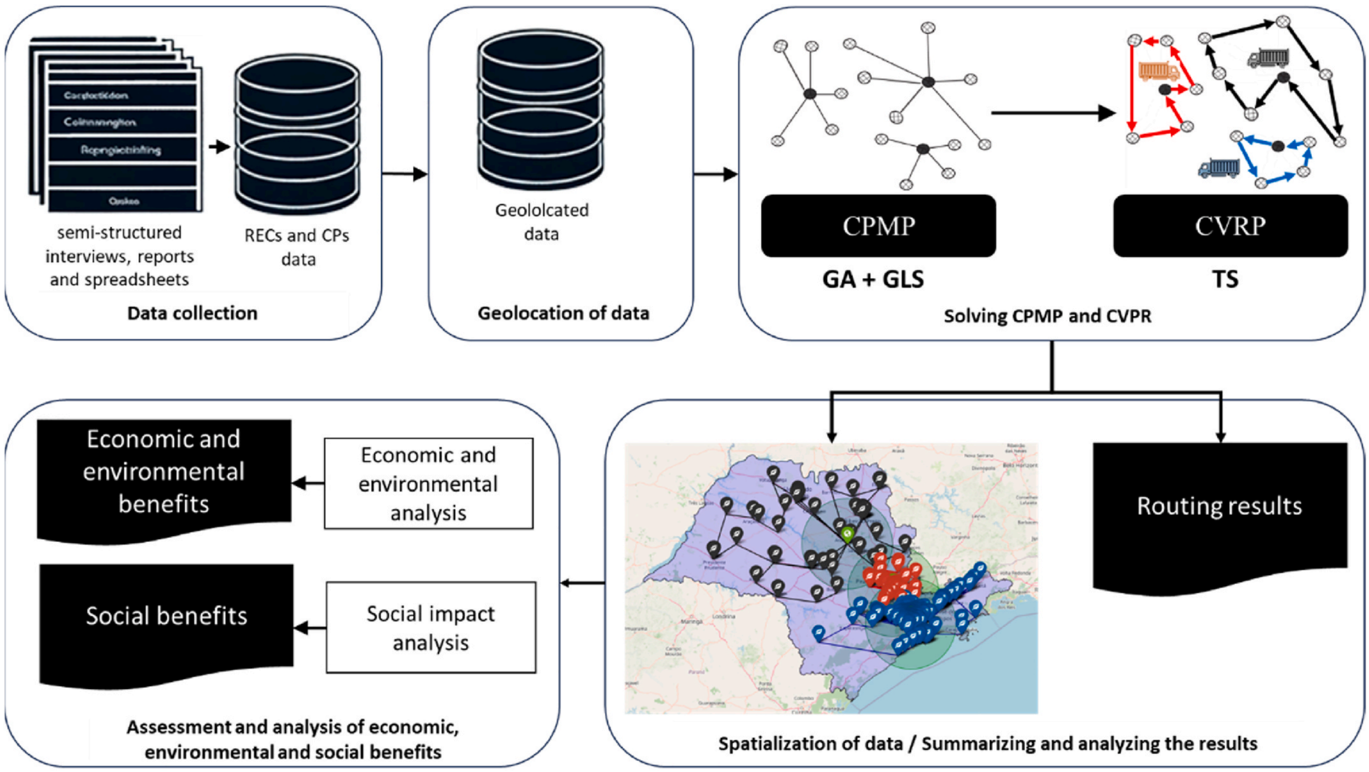


Fig. 1. Operation of the optimization approach.

$$MIC(w) = IF_A(w) + IF_B(w) + IF_C(w) + \ldots + IF_N(w) \quad (19)$$

were $IF_A(w)$,$IF_B(w)$, $IF_C(w)$, and $IF_N(w)$ represent the intensity factors of residues *A, B, C,* and *N,* respectively, in the compartment *w*.

Following this, the summation is computed for each compartment, indicating the reduction of environmental impacts in each specific area, as shown in Table 3. Subsequently, the total minimization of environmental impacts is derived by aggregating all the MICs, culminating in the total MIT, as outlined in Equation (20).

$$MIT = MIC(w) + MIC(x) + MIC(y) + MIC(z) + \ldots + MIC(n) \quad (20)$$

Equation (21) is employed to compute the decrease in emissions of major greenhouse gases and material particles produced during the transportation operation.

$$gas\ emissions = kWh{*}hours\ of\ motor\ use{*}pollutant\ gases \quad (21)$$

Considering that for an engine with a kWh rating of 75.7565, the emission rates (g/kg) for pollutant gases are as follows: carbon monoxide (CO) = 0.055, hydrocarbons (HC) = 0.023, nitrogen oxides (NO_x) = 1.746, CO_2 = 666.886, and particulate material of 0.018.

4. Results

4.1. The organizational and regulatory context of WEEE management in São Paulo, Brazil

In 2010, Brazil enacted Law 12.305/2010, which established the National Solid Waste Policy (NSWP), mandating the urgent implementation of reverse logistics and closed-loop recycling of WEEE by companies responsible for their end-of-life products. The NSWP emphasizes shared responsibility among manufacturers, RECs, and waste managers to ensure the proper return and management of WEEE, preventing contamination of the ecosystem.

The NSWP defines shared responsibility for the life cycle of products as the collective and interconnected duties of manufacturers, importers, distributors, retailers, consumers, and holders of public urban cleaning and solid waste management services. This shared responsibility aims to minimize solid waste generation and its environmental and health impacts throughout the product life cycle (Brasil. Lei nº 12.305de 2 de agosto de 2010). Article 33 of the NSWP specifically requires manufacturers, importers, distributors, and retailers of electronic products and components to establish and implement reverse logistics systems for product return after consumer use. This obligation applies independently of public waste management services (Brasil. Lei nº 12.305de 2 de agosto de 2010).

The NSWP places the responsibility for WEEE management directly on electronics manufacturers, due to their ownership of product brands. As a result, these companies faced government pressure to establish closed-loop WEEE reverse chains, driven by the significant volume of WEEE generated by the electronic sector due to excessive consumerism fueled by rapid technological advances. The Brazilian Agency for Industrial Development (ABDI – Agência Brasileira de Desenvolvimento Industrial) highlighted the emerging challenge of e-waste in Brazil, emphasizing the urgent need for WEEE reverse chains to avert potential environmental disasters caused by pollutants found in WEEE (ABDI, 2012).

Thus, electronic product manufacturers in São Paulo initiated discussions with RECs, transporters, and waste managers to promote the sectoral agreement. These meetings unveiled issues of informality in employment (informal waste pickers) within some RECs. Moreover, a lack of cohesive integration among the various links of the WEEE reverse chain was evident. For example, manufacturers lacked WEEE reverse logistics for their products at the end of their lifespan, RECs were not specialized in WEEE, instead purchasing and selling various types of waste brought by waste pickers, and there was a notable absence of specialized companies for WEEE management.

Following months of deliberations, the sectoral agreement for the shared responsibilities of WEEE management among manufacturers, waste managers, consumers/citizens, and RECs in São Paulo was successfully signed in October 2019.

However, this progress was overshadowed by the onset of the Covid-19 pandemic, which forced remote work for two years due to contamination risks, thereby delaying the practical implementation of WEEE management. It is worth noting that the selected RECs and waste managers had to adhere to labor standards, aiming to reduce informality in work and enhance the occupational health and safety of their employees. Despite these challenges, from 2022 to 2023, the WEEE reverse chain was finally organized, considering the implementation of a waste management company responsible for collection, remanufacturing, repair, reuse, recycling, and/or sale to the secondary market.

The clause 8 of the sectoral agreement emphasizes consumer participation in the system, outlining their responsibilities such as WEEE separation, removal of personal information, and proper disposal at the nearest CPs of the reverse logistics system (MMA, 2019). This underscores the significance of consumer involvement in ensuring the efficacy of WEEE reverse logistic in São Paulo. However, a challenge to this participation is the lack of information about CP locations for both consumers and local administrations. In this context, our study makes a valuable contribution by mapping the spatial distribution of CPs and RECs. This information serves as a crucial tool for decision-makers, enabling them to make informed choices regarding the expansion or reallocation of CPs and RECs to enhance WEEE collection coverage across the state of Sao Paulo.

It is worth highlighting the importance of waste management in ensuring the effectiveness of WEEE reverse logistics in São Paulo. Electronics manufacturers expressed their inability to handle simultaneous manufacturing and remanufacturing, in addition to the lack of capacity for reverse logistics, encompassing the installation of RECs and CPs near consumers and the transportation of WEEE. Consequently, a decision was made to outsource reverse logistics and remanufacturing operations to a waste manager. Subsequently, the waste manager outsourced recycling tasks to RECs that demonstrated remanufacturing capabilities and participated in the meeting, encompassing CP installation and reverse logistics. Notably, the waste manager supported RECs in the selection and identification of CPs. In this capacity, the waste manager oversees recycling operations and CP management. However, the waste manager does not possess in-house capabilities for recycling, remanufacturing, CPs, or transportation. Instead, it has established partnership with various business entities, which were endorsed in a meeting by manufacturers, government officials, and the waste manager itself. Table 4 lists various types of materials collected annually in Sao Paulo.

In Section 4.4, we examine the economic gains resulting from implementation of the optimized WEEE reverse chain, both through the increased sale of waste in secondary markets and the reduction of environmental impacts.

4.2. Preliminary computational experiments

Initially, we conducted preliminary experiments to compare the results yielded by different algorithms for solving the CPMP and CVRP. In this regard, we began by applying GA combined with GLS (GA + GLS) to address CPMP. For CVRP, we utilized the following algorithms: TS, Simulated Annealing (SA) (Benvenga et al., 2011), and GLS. Such combinations comprise solutions 1 to 3, and their results are presented in Table 5. Subsequently, recognizing that TS provided the best outcome for CVRP, we tested solutions 4 and 5, which employed the algorithms K-means (Mitchell, 1997) and self-organizing maps (SOM) (Kohonen, 1982; Haykin, 2007) to solve the CPMP. In fact, K-means and SOM neural networks are well-known algorithms for solving clustering problems.

As evident from Table 5, the solution that combines AG + GLS for addressing CPMP and TS for solving CVRP, highlighted in bold, yielded the most favorable overall outcome and was thus adopted for this study.

4.3. Optimization of WEEE reverse logistics

At the outset, the data acquired during the data collection phase—comprising REC and CP addresses and geolocations, current associations between CPs and RECs, and collection routing—was regarded as the existing scenario. In this scenario, the three RECs are positioned as follows: REC1 in São José dos Campos, REC2 in Sorocaba, and REC3 in Nova Odessa, depicted in the map shown in Fig. 3a.

Following the initial step of the CPMP solution algorithm detailed in Section 3.2.4, revised locations were proposed for the RECs: REC1 shifted to São Paulo, REC2 relocated to Araraquara, and REC3 moved to Campinas, as depicted in Fig. 3b. In the algorithm's second step, the CPs underwent redistribution. Fig. 3c portrays the current scenario wherein REC1 attends to 270 CPs marked in blue, REC2 manages 164 CPs indicated in black, and REC3 handles data collection at 120 points highlighted in red on the map. Meanwhile, Fig. 3d displays the outcome of CP redistribution to each REC following the optimization facilitated by the algorithm. In the optimized setup, REC1 now caters to 415 CPs, REC2 to 65 CPs, and REC3 to 74 CPs, totaling 554 CPs.

Fig. 4 portrays the optimized scenario, showcasing the new REC locations, CPs redistribution, and the outcomes of solving the routing problem using the TS algorithm, as elucidated in Section 3.2.4.

As delineated in Table 6, the optimization derived from the CPMP and CVRP solutions resulted in a 30.48 % reduction in distances covered to service all CPs, equating to 4681 km. Additionally, there was a reduction of approximately 50 h in the time required for collections, signifying a 20.69 % improvement. It is noteworthy that these distances and times were computed following the methodology expounded in Oliveira Neto (Oliveira Neto et al., 2023a,b).

In the optimized scenario data, it is evident that REC1 experienced a notable 54 % increase in the number of CPs served, yet still achieved a slight reduction (58 km) in routing distances. This outcome is attributed to REC1's new location, underscoring the significance of optimization. For RECs 2 and 3, there were reductions of 60 % and 38 %, respectively, in the number of CPs served, also influenced by their relocations. Comparing REC2's routing distances depicted in black in Fig. 4, despite servicing widely distributed CPs, there's a decrease of 393 km observed. Notably, REC3 displays a substantial discrepancy (a reduction of 4681 km) in the total routing distance, contributing significantly to the overall optimization of the new scenario, even with the need to add 2 vehicles to the fleet, as indicated in Table 6, due to the relocation of RECs and redistribution of CPs.

In terms of collection times, it is noticeable that gains were only evident in REC3, while REC1 and REC2 showed slight increases. Despite these increments in collection times for the latter two RECs, an overall reduction of over 20 % in total working time was observed when comparing the current and optimized scenarios. This emphasizes the importance of approaching the problem holistically rather than considering the RECs individually.

The decreases in distances and collection times through optimized vehicle routing play a pivotal role in achieving significant environmental benefits. Optimized routes offer substantial reductions in pollutant emissions, fuel consumption, and consequently, the carbon footprint linked to transportation activities. This routing efficiency not only aids environmental preservation but also leads to considerable savings in natural and financial resources. Furthermore, optimization fosters a more sustainable and efficient management of reverse logistics, aligning with sustainability practices and objectives aimed at environmental responsibility, aspect important to promote strong sustainability (Pinto et al., 2020).

Lastly, it is crucial to underscore that research in this domain often involves intricate optimization algorithms employing AI. However, there is frequently a lack of detailed explanations regarding the problems and adopted solutions, unlike the comprehensive approach outlined in this research. In this regard, the produced maps serve to enhance operations managers' comprehension of the optimization process,

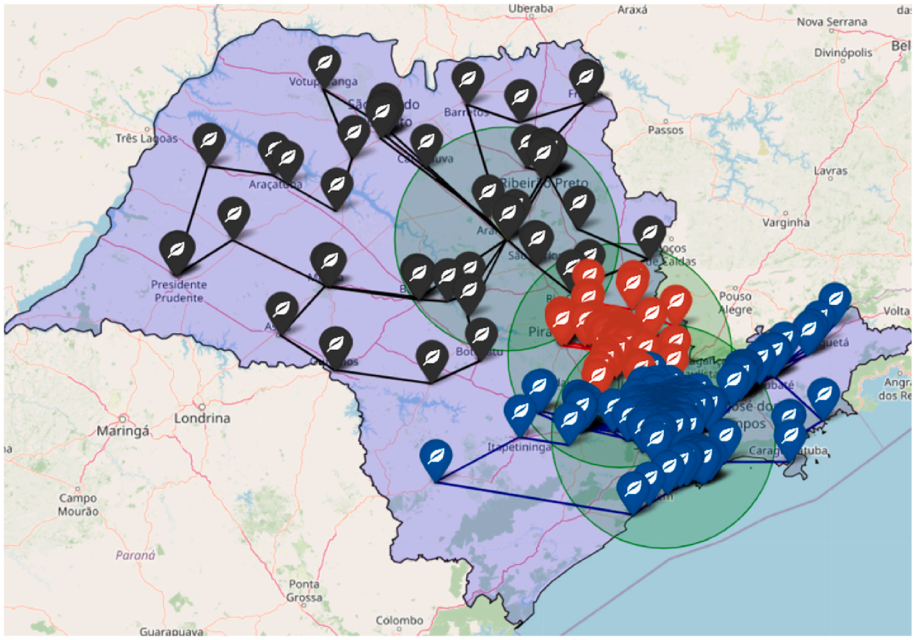


Fig. 2. Map-based visualization of the integrated CPMP and CVRP results.

contributing to more informed decision-making.

4.4. Economic and environmental assessment

Relocating a company's headquarters to another city within the same state involves several associated expenses. These include (A) company closure costs, (B) documentation expenses—such as amendments to articles of incorporation, inspection fees, location and operation charges, permits, and feasibility analyses—and (C) transportation expenses (JUCESP, 2020; ANTT, 2023). For calculating (A), the average area of companies involved in electronic waste recycling in Brazil was considered to be 2200 square meters (Raab, 2020). In the case of REC1 (from São José dos Campos to São Paulo), the overall estimated cost amounted to R$ 7679.19, with (A) accounting for approximately R$ 2000.00, (B) for around R$ 4000.00, and (C) totaling R$ 1679.19.

The differences between REC2 and REC3 are exclusively due to transportation expenses. The freight cost for transferring companies from Sorocaba to Araraquara is R$ 3,426, while from Nova Odessa to Campinas it is R$ 945.30. Therefore, the total estimated cost for relocating all RECs would amount to approximately R$ 24,051.00. The projected expenses could be deemed insignificant. When considering solely the freight cost per kilometer for relocating the headquarters at R$ 15.64, and contrasting it with the saved distance of 4681 km (which reflects a 30.48 % optimization), the result would yield a positive balance of R$ 49,140.00.

Table 7 shows the reduction in environmental impacts based on the annual volume of WEEE collected in São Paulo, segregated and sold in the secondary market, with a 10 % loss considered, as provided by the researched expert. Among the collected waste, 32 % comprised iron, 22.9 % plastic, 12.2 % copper, 10.9 % aluminum, 6 % steel, and 6 % printed circuit boards. These circuit boards were further dismantled and sorted based on their components to facilitate environmental assessment.

Additionally, Table 7 showcases the optimization of the WEEE reverse chain in São Paulo state. Through simulation using the method that combines GA and GLS, it was possible to identify the strategic locations for the three RECs. This enabled the determination of the most efficient optimized scenario, reducing the consumption of diesel and engine oils and coolant fluid (ethylene glycol).

This optimized scenario resulted in a reduction of abiotic environmental impacts totaling 621547.5 t/year, encompassing global warming, rainfall, relief, and humidity. Furthermore, optimized environmental impacts on water reduced by 3855987 t/year and air by 93208.31 t/year. However, during the process of washing WEEE, RECs consume 154 kWh of electricity and 161 t of water annually, leading to an increase in environmental impacts of 9657.27 t/year.

Although the consumption of natural resources (water and electricity) during the washing of electrical and electronic waste led to an increase in certain environmental impacts, the overall MIT remained positive, totaling 4561086 t/year.

In addition, the reduction in gas emissions was measured with the optimized scenario, which includes CO, HC, NO_x, CO_2 and particulate material for one truck and for the fleet of 57 trucks. For this evaluation, the guidelines of the EPA (2021) and ICCT (2021).

The outcomes presented in Table 8 demonstrate a decrease in emissions, totaling 1721047.74 kg/year of atmospheric pollutants after the optimization of the WEEE reverse chain in São Paulo, considering the fleet of 57 trucks.

Consequently, there was a reduction in CO_2 emissions by approximately 1716297.93 kg/year. It is crucial to highlight that excessive inhalation of CO_2 impedes the circulation and distribution of oxygen, vital for human life.

Moreover, there was a reduction in airborne particulate matter from 233.7 to 177.84 kg/year. These particles significantly impact health,

Table 4
Volume of WEEE collected per year in Sao Paulo.

Material	Annual Mass (ton)	Material	Annual Mass (ton)
ABS Plastics	2533.3	Aluminum	839.3
Iron	2464	Nickel	35.105
Glass	52000	Lead	32.107
Copper	939.4	Tin	31.318
Styrene/ butadiene	37.2	Zinc	31.121
Ferrite	31.566	Polypropylene	116.345
Stainless steel	202	Polycarbonate	28.565
Low alloy steel	462	PVC	32.517
Silver	32.4	Pottery	27.46
Gold	1.252	Fiberglass (resistive)	23.803
Palladium	1.25		

Table 5
Comparison of the results obtained by the algorithms tested for the CPMP and CVRP solutions.

Problems	Solutions				
	1	2	3	4	5
CPMP	**AG + GLS**	AG + GLS	AG + GLS	K-means	SOM
CVRP	**TS**	SA	GLS	TS	TS
Total routing (in km)	**10679**	10754	10922	13143	14154

potentially causing various lung and heart diseases. Although this study reported a modest decrease of only 55.86 kg/year, wider adoption of transport operation optimizations by more companies could substantially increase this reduction.

The study also revealed a decline in NO_x emissions by 4493.31 kg/year. Additionally, there was a reduction of CO, a gas resulting from the combustion of self-propelled engines, possessing considerable toxicity potential, by 141.36 kg/year.

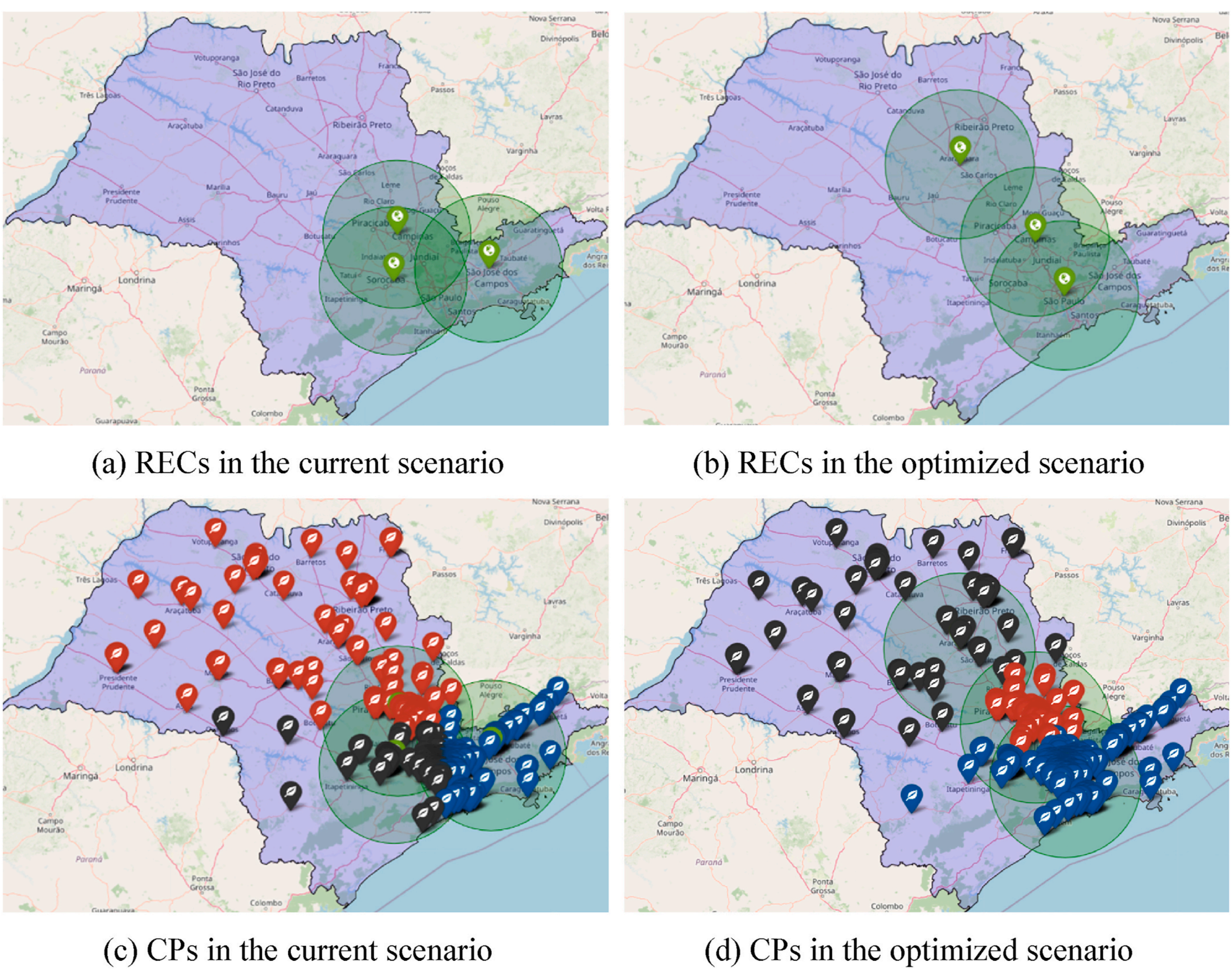
Lastly, HC decreased by approximately 59.28 kg/year. HC represents the unburned or partially burned fuel expelled by the engine, along with fuel vapor emitted from different points of the vehicle or during tank filling.

4.5. Positive social implications

The optimization of the WEEE reverse chain, in addition to the previously mentioned economic and environmental gains, also generates significant benefits for waste pickers—a socially vulnerable group. Their involvement in sorting and recycling operations, combined with adequate training and improved working conditions, not only enhances operational efficiency but also promotes social and economic inclusion.

Aligning with the NSWP, RECs and CPs promote responsible and collaborative management within the reverse WEEE chain, contributing to several SDGs established by the UN. This alignment includes eradicating poverty (SDG 1) by involving waste pickers in recycling operations, reducing poverty, and fostering economic stability. It also addresses decent work and economic growth (SDG 8), creating safer and more equitable conditions for waste pickers, along with reducing inequalities (SDG 10) by generating job opportunities for their social inclusion.

Contributions extend to sustainable cities and communities (SDG 11) through waste pickers' involvement in recycling activities, fostering more effective waste management. The recycling and reuse of materials further align with responsible consumption and production (SDG 12), curbing the extraction of virgin materials. Partnerships and cooperation (SDG 17) among players like manufacturers, waste management, RECs, and CPs also contribute significantly to implementing the WEEE reverse



(a) RECs in the current scenario
(b) RECs in the optimized scenario
(c) CPs in the current scenario
(d) CPs in the optimized scenario

Fig. 3. Locations of RECs and distribution of CPs in current and optimized scenarios.

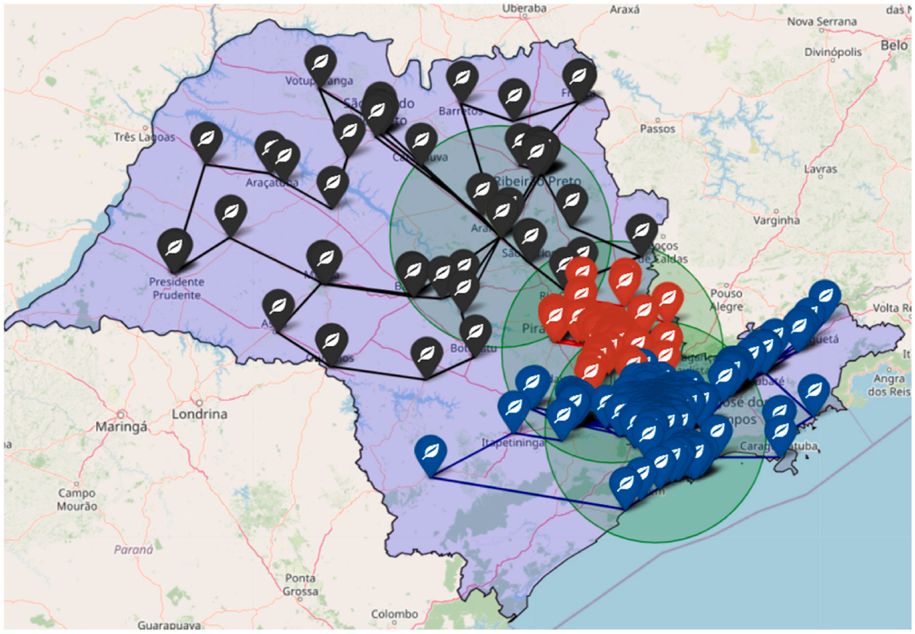


Fig. 4. Visualization of optimized scenario for WEEE reverse logistics.

Table 6
Comparative analysis of current and optimized scenario data.

REC	Current scenario				Optimized scenario			
	Number of CPs	Traveled distance (km)	Collection time (s)	Number of vehicles	Number of CPs	Traveled distance (km)	Collection time (s)	Number of vehicles
REC1	270	6339	381099	28	415	6281	396312	43
REC2	164	3730	204427	16	65	3337	227131	6
REC3	120	5291	279908	11	74	1061	62962	8
Total	**554**	**15360**	**865434**	**55**	**554**	**10679**	**686406**	**57**
Summary								
Total		Distance	Time			Distance	Time	
per month		15360 km	240h:23m:54s		10679 km		190h:40m:06s	
per year		184320 km	2884h:46m:48s		128148 km		2288h:01m:12s	

chain.

This study has shown that optimizing the WEEE reverse supply chain goes beyond mere economic gains—it should also contribute to reducing socio-environmental impacts and aligning with multiple SDGs. These include improving health and well-being (SDG 3) by minimizing exposure to toxic substances found in WEEE, combating global climate change (SDG 13) through optimized transportation that lowers greenhouse gas emissions, and preserving life below water (SDG 14) and life on land (SDG 15) by preventing environmental contamination. The implementation of efficient technologies in WEEE management empowers RECs to play a pivotal role in advancing these global sustainability targets.

5. Discussion

This study optimized the WEEE reverse logistics chain in São Paulo, Brazil, by reallocating recyclers, redistributing collection points, and minimizing collection distances and times. Employed AI-based algorithms demonstrated superior performance compared to other methods, achieving a 30.48 % reduction in annual travel distance (from 184,320 to 128,148 km) and saving 596 h and 45 min per year in collection time. While most previous studies—such as those from Greece (Achillas et al., 2010b), the USA (Assavapokee and Wongthatsanekorn, 2012), and China (Qiang and Zhou, 2016)—primarily focus on either route optimization or facility placement, this work integrates both dimensions. It emphasizes the strategic importance of locating CPs close to users prior to determining REC locations. The findings underscore the potential of AI technologies to enhance reverse logistics systems by supporting economic growth, empowering local recyclers, and advancing sustainable development goals, in alignment with the NSWP. In addition to the positive economic assessment, this study also presents environmental and social benefits aligned with the UN SDGs—an innovative contribution to a field largely dominated by research focused on cost reduction through transportation efficiency.

Following the optimization, an environmental assessment was conducted using the MIF within the reverse logistics, considering the total volume of WEEE collected in São Paulo, based on data provided in the literature (de Oliveira Neto and de Sousa, 2014; De Oliveira Neto et al., 2015; De Oliveira Neto and Lucato, 2016). This assessment revealed significant environmental benefits, including reductions of 621,547.5 tons/year in abiotic resource use, 3,855,987 tons/year in water consumption, and 93,208.31 tons/year in air pollutant emissions. Additionally, atmospheric pollutants such as CO, HC, NO_x, CO_2, and particulate matter were reduced by 30,193.82 kg/year. These results enabled the construction of a physico-chemical mass balance. However, the optimization also led to increased electricity consumption (154 t/kWh) and water use (161 tons/year), resulting in a net negative environmental impact of 9657.27 tons/year in these specific categories. Despite these trade-offs, the overall positive MIT reached 4,561,086 tons/year. These findings go beyond those of previous WEEE logistics

Table 7
Material intensity assessment.

Components	Annual Mass (t/kWh)	Abiotic	Biotic	Water	Air	Annual Reduction (t)
ABS Plastics	2533.3	10057.2		524114.4	9499.875	543671.5
Iron	2464	53173.12		1243975	12492.48	1309641
Glass	52000	153400		605800	38480	797680
Copper	939.4	327352.7		344910.1	1503.04	673765.9
Styrene/butadiene	37.2	212.04		5431.2	61.38	5704.62
Ferrite	31.566	23611.37		40593.88	299.877	64505.12
Stainless steel	202	1902.84		15226.76	131.3	17260.9
Low alloy steel	462	679.14		27147.12	240.24	28066.5
Silver	32.4	243				243
Gold	1.252	676.08				676.08
Palladium	1.25	400.3763		240.91	17215	17856.29
Aluminum	839.3	15929.91		452559	4960.263	473449.1
Nickel	35.105	4959.985		8191.401	1433.337	14584.72
Lead	32.107	581.7788		4360.131	73.20396	5015.113
Tin	31.318	265.7645		343182.6	4666.382	348114.8
Zinc	31.121	718.8951				718.8951
Polypropylene	116.345	243.1611		4165.151	172.1906	4580.503
Polycarbonate	28.565	198.2411		6061.207	134.2555	6393.704
PVC	32.517	112.834		9927.115	55.2789	10095.23
Pottery	27.46	57.9406		157.6204	1.373	216.934
Fiberglass (resistive)	23.803	258.0245		7051.639	47.84403	7357.507
Diesel oil	18725	25466		181632.5	374.5	207473
Engine Oil	294	441		3366.3	887.88	4695.18
Coolant Fluid (Ethylene Glycol)	209	606.1		27893.14	478.61	28977.85
Environmental impact reduction		621547.5		3855987	93208.31	4570743
Electricity	154	485.1	6.16	8876.56	78.54	9446.36
Water	161	1.61		209.3	0	210.91
Environmental impact increase		486.71	6.16	9085.86	78.54	9657.27
MIC (annual)		621060.8	−6.16	3846901	93129.77	
MIT (annual)						4561086

studies, which have primarily focused on CO_2 reductions associated with shorter collection routes (e.g., Moslehi et al., 2021; Oliveira Neto et al., 2023a,b; Guo and Zhong, 2023), and expand the discussion to encompass a broader set of environmental indicators. While some studies have addressed environmental compliance (Tosarkani et al., 2020; Llerena-Riascos et al., 2021; Lv and Du, 2021) or landfill diversion (Achillas et al., 2010b; Tosarkani et al., 2020; Moslehi et al., 2021), and others have mentioned fuel savings (Oliveira Neto et al., 2023a,b), few have employed comprehensive environmental metrics as presented here.

Beyond environmental outcomes, the optimization of São Paulo's WEEE reverse chain also reinforced RECs as sustainable infrastructures and highlighted the social benefits achieved. This complements prior research on social dimensions of reverse logistics, such as job creation (Shokouhyar and Aalirezaei, 2017; Bal and Satoglu, 2018; Safdar et al., 2020; Najm and Asadi-Gangraj, 2024), local development (Shokohyar and Mansour, 2013; Chen et al., 2024), and workplace safety (Guo and Zhong, 2023). By employing AI-driven optimization, the study underscored the critical role of waste pickers in facilitating WEEE collection and recycling in Brazil. These strategies directly contribute to local development, poverty reduction, and the formation of sustainable communities, while supporting responsible consumption and production practices.

The social outcomes observed are closely aligned with several SDGs and offer a roadmap for other regions. Job formalization in WEEE recycling and transportation contributes to poverty alleviation (SDG 1), economic growth (SDG 8), and reduced inequality (SDG 10). By shifting informal work into formal employment, workers benefit from fair wages and improved living conditions. Additionally, prioritizing local development positions São Paulo as a model for sustainable urban planning (SDG 11) by addressing environmental pressures on water, land, and climate (SDGs 13–15). These efforts promote broader community benefits such as improved health, well-being, and inclusive development. The optimized reverse chain in São Paulo helps prevent environmental degradation—especially water and soil contamination—and supports climate change mitigation. These achievements reflect a broader vision of building responsible, socially conscious societies. By extending these findings to other contexts, stakeholders can develop integrated solutions that balance economic, environmental, and social goals in WEEE management.

In broader contexts, such as municipal solid waste management—as addressed by Boonmee et al. (2021) and Nikonorov et al. (2021)—and post-disaster waste management, as investigated by Boonmee et al. (2023), the approach proposed in this study can be employed as a strategic tool to optimize the location of recycling centers and collection

Table 8
Reduction in gas emissions.

Gases	Average Emission (g/kWh)	Current Scenario kg/year (one truck)	Current Scenario kg/year (one truck)	Optimized Scenario kg/year (one truck)	Optimized Scenario kg/year (fleet of 57 trucks)	Emission Reduction kg/year (one truck)	Emission Reduction kg/year (fleet of 57 trucks)
CO	0.055	12.02	685.14	9.53	543.21	2.48	141.36
HC	0.023	5.03	286.71	3.99	227.43	1.04	59.28
N_{ox}	1746	381.47	21743.79	302.64	17250.48	78.83	4493.31
CO_2	666,886	145702.42	8305037.94	115591.93	6588740.01	30110.49	1716297.93
Particulate material	0.018	4.10	233.7	3.12	177.84	0.98	55.86
Total Emissions		**146105.03**	**8327986.71**	**115911.21**	**6606938.97**	**30193.82**	**1721047.74**

Considering an engine kWh of 75.7565, 2884 h/year worked in the current scenario and 2288 h/year worked in the optimized scenario.

points, as well as vehicle routing. By using AI-based techniques and optimization models, our approach enables the integration of economic and environmental aspects to promote operational efficiency, social gains, reduce logistical costs, and improve collection coverage.

Although real-world variables such as dismantling costs, traffic conditions, and operational delays were not modeled, the simulated ideal conditions provide a solid foundation for future refinements that could incorporate dynamic logistical constraints. Additionally, while the dataset was limited to a subset of companies and recyclers, it included key regional actors and offers a scalable and adaptable framework for broader applications. Furthermore, although the social and environmental metrics were partially simplified, their inclusion underscores critical impacts—such as job creation, improved working conditions, and emissions reduction—aligned with the UN SDGs. Future developments could benefit from the incorporation of dismantling costs, assessing the social effects of reduced demand for transport labor, and exploring the role of formal employment in mitigating social inequalities represent key directions for enhancing the social and economic dimensions of WEEE reverse logistics modeling. Altogether, these enhancements would support the development of a more holistic and robust framework for sustainable urban waste management. It is worth noting, however, that such simplifications are common in early-stage studies and do not diminish the contribution of this study in demonstrating how AI-based optimization can effectively promote both efficiency and sustainability in reverse logistics systems.

6. Conclusion

This research demonstrates that applying AI-based techniques, namely GA, GLS, and TS, can significantly enhance the reverse logistics process for managing reverse logistics of WEEE in São Paulo. By optimizing the placement of RECs, redistributing CPs and optimizing the vehicle routing, the study achieved notable reductions in travel distances (30.48 %) and collection times (over 20 %), resulting in lower operational costs and environmental benefits, including the mitigation of more than 4.56 million tons/year in impacts: 621,547 tons in abiotic resources, 3.855 million tons in water usage, and 93,208 tons in atmospheric emissions. Greenhouse gas emissions, including CO_2 and NOx, were reduced by over 30 tons annually. These outcomes highlight WEEE optimization's importance in minimizing the carbon footprint, as evidenced by environmental assessments using the MIF.

Furthermore, the study emphasizes the social benefits of efficient reverse logistics networks, such as job creation and improved working conditions for waste pickers and recycling workers, aligning economic and environmental objectives with community welfare and local development. Using spatial data visualization tools, such as OpenStreetMap, enhances decision-making by enabling accessible and user-friendly planning for waste management systems.

Our AI-based optimization approach can serve planners as a practical tool to improve the efficiency of WEEE reverse logistics by identifying optimal locations for RECs, improving WEEE collection coverage, and providing routing strategies. It supports data-driven decisions that reduce costs and emissions, in alignment with circular economy goals, environmental compliance standards, and the UN SDGs. The approach also helps anticipate social and environmental impacts, contributing to more effective and equitable municipal waste policies.

Future work could enhance the mathematical optimization model of the WEEE reverse logistics chain by directly incorporating economic, environmental, and social gains, considering not only common variables such as distances, times, and transportation costs, but also dismantling costs for recyclers, as well as broader social and environmental impacts. These may include indicators related to carbon tax policies, as presented by Boonmee et al. (2021), or the quantitative indicators proposed by Bruno et al. (2021). Additionally, future studies should consider incorporating sensitivity analyses to evaluate the robustness of the model under varying scenarios, along with practical parameters such as operational constraints and dynamic demand patterns, which are essential for real-world implementation. Further explorations—such as assessing the role of formal job creation in reducing social inequalities and analyzing community development outcomes resulting from decreased environmental burdens—could also significantly contribute to advancing sustainable waste management practices.

Funding

This research was supported by FAPESP (Fundação de Amparo à Pesquisa do Estado de São Paulo) (Proc. 2020/16364-5) and CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico) Universal Project 2023 (Proc. 409321/2023-0). The funding institutions had no involvement in the study design; collection, analysis and interpretation of data; writing of the report; and in the decision to submit the article for publication.

CRediT authorship contribution statement

Geraldo C.de Oliveira Neto: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Rodrigo Neri Bueno da Silva:** Writing – review & editing. **Gustavo Araújo Lima:** Software, Methodology. **Sidnei Alves de Araújo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis. **Peterson Adriano Belan:** Software, Methodology, Formal analysis. **Denilson Carvalho:** Writing – review & editing. **Cecília M.V.B. Almeida:** Writing – review & editing, Writing – original draft, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1

GA was selected due to its widespread use in optimizing highly complex problems. An additional advantage of GA is its facilitation of implementing hybrid approaches, such as the one proposed here. Finally, the results obtained in comparative tests with other algorithms (see Table 5) corroborate its effectiveness.

Proposed algorithm to solve CPMP

Begin

Let *s'* be the best solution of the current generation, s* *the best solution* obtained, GEN the counter of the number of generations, MAX_GEN the maximum number of generations allowed, and MAX_NGWI the maximum number of generations without improvement.

(*continued on next page*)

(*continued*)

```
  MAX_GEN ← 1000
  MAX_NGWI ← 50
  GEN ← 1
  Generate the initial population applying Greedy Local Search (GLS) algorithm
  Evaluate the population based on equations (1) to 7)
  While (GEN ≤ MAX_GEN) and (MAX_NGWI was not reached)
    Select the best individuals
    Make the crossover with the best individuals to compose the new population (considering the crossover probability)
    Make the mutation (considering the mutation rate)
    Evaluate the population based on equations (1) to 7)
    If s' > s* then
      s*s ← '
    End If
      GEN ← GEN + 1
  End While
  Return s*
End
```

Appendix 2

TS was chosen due to its inclusion in the OR Tools package. In addition, the results obtained in comparative tests with other algorithms (see Table 5) corroborate its selection. It's important to note that the parameterization of the TS algorithm adheres to the standard settings defined within the OR-Tools library.

Proposed algorithm to solve CVRP

```
Beginning
  Let s0 be the initial solution (randomly generated routing), s be the solution represented by the current state, s' be the
  solution represented by the best neighbor of the current state, s* be the best solution obtained so far, Iter be the counter
  of the number of iterations, Melhor_Iter the most recent iteration that provided s*, Max_Iter_sm the maximum number of
  iterations with no improvement of s*, and T the taboo list. Equations (10)–(16) are employed to evaluate of the
  solutions.
  T ← ∅
  S* ← S0
  s ← s0
  Iter ← 1
  Melhor_Iter ← 1
  Max_Iter_sm ← 50
  T ← T ∪ s0
  As long as (Iter – Melhor_Iter ≤ Max_Iter_sm) Do
    Select successor s' {s' ∉ T }
    s ← s'
    T ← T ∪ s
    If f(s) > f(s*) Then
      S*S ←
      Melhor_Iter ← Iter
    End Up
    Iter Iter ← + 1
  End-as
  Return s*
End
```

Appendix 3

1 - REC opening and closing costs

Fees	Company opening (RS$)	Company closure (RS$)
Social contract	158	
Inspection	21	
Operation	150	
Permit	120	
Others	3520	
Total	3963	2000

2 Estimation of freight costs for RECs relocation

APPROXIMATE FREIGHT COSTS FOR RECs RELOCATION					
ITEM	REC	Current city	New destination	km	Fr Freight cost
1	REC1	São José dos Campos	São Paulo	100	R$ 1.679,19
2	REC2	Sorocaba	Araraquara	250	R$ 3.426,55
3	REC3	Nova Odessa	Campinas	37	R$ 945,30
TOTAL				387	R$ 6.051,04

VALUES CALCULATED ACCORDING TO ANTT RESOLUTION NO. 5867/2020, AS UPDATED BY PORT. SUROC N°20/2023	
Details	
1	Transport Operation: Table A - Road Transport of Cargo and Capacity Distance: 100 km Displacement Cost Factor (CCD): 6.0672 Loading and unloading cost coefficient (CC): 514.29 One Way Value = (Distance x CCD) + DC: 1121.01 Empty return value (if any) = 0.92 x Distance x CCD: 558.18
–	
2	Transport Operation: Table A - Road Transport of Cargo and Capacity Distance: 250 km Displacement Cost Factor (CCD): 6.0672 Loading and unloading cost coefficient (CC): 514.29 One Way Value = (Distance x CCD) + CC: 2031.09
–	
3	Transport Operation: Table A - Road Transport of Cargo and Capacity Distance: 37 km Displacement Cost Factor (CCD): 6.0672 Loading and unloading cost coefficient (CC): 514.29 One Way Value = (Distance x CCD) + CC: 738.78 Empty return value (if any) = 0.92 x Distance x CCD: 206.53
–	
	The freight simulator of the National Land Transport Agency (ANTT) was used
	Available at: https://calculadorafrete.antt.gov.br/

Data availability

Data will be made available on request.

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