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Operations Research in Municipal Solid Waste Management: Decision-Making Problems, Applications, and Research Gaps

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Abstract. Municipal Solid Waste Management (MSWM) represents a complex, multi-level decision domain that involves strategic, tactical, and operational planning under economic, environmental, and social constraints. This paper reviews the state of Operations Research (OR) applications to MSWM. The analysis encompasses optimization, simulation, metaheuristic, and hybrid approaches that address decision problems ranging from facility siting and capacity expansion to routing and scheduling. The study classifies OR contributions across decision levels, identifying methodological patterns and dominant model types such as mixed-integer programming, metaheuristics, and simulation-optimization frameworks. Despite significant progress in optimization and the integration of sustainability, critical gaps remain in uncertainty modeling, system-wide integration, and data-driven decision support. Deterministic formulations prevail at the strategic and tactical levels, while uncertainty is mainly explored in operational routing. Cross-level coordination among infrastructure planning, fleet design, and daily operations remains underdeveloped. Furthermore, persistent data scarcity and the limited incorporation of behavioral factors constrain the practical applicability of OR models. The review concludes with a research agenda that advocates for multi-level, uncertainty-aware, and dynamic optimization frameworks, supported by standardized data infrastructures and behavioral insights.

Keywords: Municipal Solid Waste Management, Operations Research, optimization, vehicle routing, stochastic modeling, simulation-optimization, multi-objective decision making, sustainability, uncertainty

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1. THE GLOBAL IMPERATIVE FOR OPTIMIZED MUNICIPAL SOLID WASTE MANAGEMENT

Municipal Solid Waste Management (MSWM) has emerged as a significant global challenge, driven by the relentless forces of rapid urbanization, population growth, and shifting consumption patterns. Ineffective MSWM poses severe threats, contributing to public health issues, environmental degradation, and the depletion of natural resources. The scale of this crisis is staggering, with global MSWM production surpassing 2 billion tons annually. Without decisive action, projections suggest this figure could double to approximately 4 billion tons by 2100. This trajectory highlights the pressing need for robust, structured, and strategic-level decision-making frameworks.

The complexity of MSWM extends far beyond a simple technical problem. It is a multi-dimensional system encompassing a wide range of interconnected economic, environmental, and social factors. The entire waste value chain – from generation and collection to treatment and disposal – presents numerous decision points that require sophisticated analysis to ensure sustainability. In this context, decision-making cannot rely on reactive, ad-hoc measures. Instead, it requires a proactive and comprehensive approach that can balance conflicting objectives, such as minimizing costs, reducing environmental footprints, and ensuring social acceptability.

Operations Research (OR) offers a foundational discipline for addressing the intricate decision-making problems inherent in MSWM. By employing mathematical modeling, optimization techniques, and various algorithms, OR provides a powerful toolkit for analyzing complex systems and identifying optimal or near-optimal solutions. Application of OR techniques can lead to significant cost savings and improved waste recovery, making them a crucial component of any modern waste management system (Ghiani et al., 2014). Within this framework, a broad array of OR techniques has been developed to address the diverse decision-making challenges of MSWM, ranging from optimization-based planning to simulation and hybrid methods. Optimization models dominate at the strategic and tactical levels, where Mixed-Integer Programming (MIP) and decomposition techniques have been widely employed for facility location, network design, and multi-objective trade-offs (Ghiani et al., 2014). Rich MIP formulations also appear in Vehicle Routing Problems (VRPs) for selective waste collection, incorporating facility and material compatibility constraints (Korcyl et al., 2019). Simulation models, both discrete and continuous, have been used to evaluate MSWM system performance and design recycling programs under operational-level variability (Antmann et al., 2013). Metaheuristics and matheuristics represent the state of practice for the Waste Collection and Routing Problems (WCRP), with algorithms such as Ant Colony Optimization (ACO), Simulated Annealing (SA), Genetic Algorithms (GA), Large Neighborhood Search (LNS), Greedy Randomized Adaptive Search Procedures (GRASP), and Adaptive Large Neighborhood Search (ALNS) – often in hybrid configurations (Han & Ponce-Cueto, 2015; Xu et al., 2015). Examples include sectoring-routing local search approaches (Cortinhal et al., 2016) and hybrid ACO-SA models with Taguchi parameter tuning (Tirkolaee et al., 2020). Simulation-optimization frameworks (simheuristics) have emerged to address stochastic travel times and time-dependent routing by embedding Monte Carlo simulation within metaheuristic search (Gruler et al., 2020). Finally, uncertainty modeling remains a challenge: fuzzy chance-constrained formulations have been proposed for demand uncertainty (Tirkolaee et al., 2020), and stochastic travel conditions are commonly handled through simulation (Gruler et al., 2020); yet, comprehensive end-to-end stochastic optimization formulations across decision levels are still limited, as several reviews have noted (Tirkolaee et al., 2018).

The literature provides solid strategic-tactical-operational level framing for MSWM primarily via broad surveys (Asefi et al., 2020; Ghiani et al., 2021) and a deep, globally oriented operational-level routing corpus (Beliën et al., 2014; Han & Ponce-Cueto, 2015), with uncertainty and hybrid sim-opt demonstrated mainly at the operational level (Antmann et al., 2013; Gruler et al., 2020; Tirkolaee et al., 2020), but it lacks an explicit end-to-end, uncertainty-aware, multi-level optimization synthesis with a formal problem-method matrix. Therefore, this work provides a review of the state of OR applications in MSWM, with a specific focus on the body of knowledge published through 2021. The aim is to systematically analyze and synthesize the existing literature, distinguishing between strategic, tactical, and operational decision-making problems in municipal solid waste management through the lens of OR. A central objective is to identify and articulate the key research gaps and limitations that existed in the field at that time, thereby providing a clear agenda for future research. The review focuses on studies that apply optimization, simulation, metaheuristics, or hybrid approaches, particularly those addressing uncertainty in decision-making processes. This analysis not only documents progress but also highlights the critical areas where traditional OR models fall short, thereby paving the way for more integrated and practical solutions. In addition to methodological and hierarchical dimensions, two cross-cutting challenges are increasingly evident in the recent literature: (1) the limited integration of behavioral and social factors influencing waste generation and participation, and (2) persistent data quality and infrastructure constraints that affect the calibration and implementation of OR models. These issues shape the practical feasibility of optimization frameworks and are therefore taken into account when identifying the main research gaps. The review focuses on peer-reviewed studies published between 2000 and 2021, collected primarily through targeted searches in Semantic Scholar, ScienceDirect, Scopus, and Google Scholar. The selection emphasizes works applying optimization, metaheuristics, simulation, or hybrid analytical approaches to municipal solid waste management decision problems. Studies were included if they (1) explicitly formulated the problem using OR techniques and (2) addressed decisions at the strategic, tactical, or operational level. Classic foundational works were retained where they continue to serve as methodological reference points. Publications after 2021 were not systematically reviewed; therefore, emerging topics such as fleet electrification, dynamic and online routing, and IoT-enabled real-time optimization are acknowledged as relevant but fall outside the temporal scope of this study. This clarification ensures the analytical consistency of the review period.

Three research questions guide the investigation:

- RQ1: How have MSWM decision problems been classified and modeled across the strategic, tactical, and operational levels?
- RQ2: Which OR problem classes, methodological families, and uncertainty modeling approaches dominate at each level?
- RQ3: What forms of methodological integration exist across decision levels, and what gaps remain in end-to-end, multi-objective, and uncertainty-aware modeling?

The review does not claim to be exhaustive. Instead, it focuses on representative studies that reflect the dominant modelling approaches and methodological developments in the period examined. The review encompasses peer-reviewed journal articles and full conference papers published in English prior to October 31, 2021. Eligible studies focus on municipal solid waste management systems covering at least one central process stage – generation, collection, transfer, treatment, or disposal – and employ recognized OR methodologies. Optimization models (e.g., MIP, Mixed-Integer Quadratic Programming (MIQP), decomposition), simulation approaches (discrete-event or system dynamics), metaheuristic algorithms, and simulation-optimization hybrids are all eligible for inclusion. Studies must also exhibit methodological generalizability beyond single-city applications or explicitly incorporate uncertainty through stochastic, robust, fuzzy, or chance-constrained formulations.

Papers were excluded if they focused solely on non-municipal waste streams, such as industrial, hazardous, or electronic waste; if they lacked a formal optimization component, such as purely Internet of Things (IoT), Geographic Information System (GIS), or Multiple-Criteria Decision Analysis (MCDA) applications; or if they addressed isolated processes, like waste-to-energy plants or market analyses, without broader system optimization. Algorithmic studies without a substantive connection to MSWM planning were also omitted.

The primary search was conducted using the Semantic Scholar, PubMed, and arXiv databases to cover as many papers as possible, including those not indexed in Scopus or Web of Science. Searches combined waste management and OR terminology using Boolean structures such as: "municipal solid waste" OR "solid waste" AND (optimization OR simulation OR "operations research" OR "stochastic" OR "robust" OR "metaheuristic" OR "chance constrained") AND (strategic OR tactical OR operational OR routing OR siting OR "network design" OR "capacity expansion"). The time window extended from database inception to the end of 2021, and only peer-reviewed English-language publications were retained. Additional material was identified through backward and forward snowballing from established reviews and methodological anchors, such as Beliën et al. (2014), Ghiani et al. (2014), and Asefi et al. (2020).

2. A TAXONOMY OF OPERATIONS RESEARCH APPLICATIONS IN MSWM

This section establishes a structured framework for understanding the field by categorizing OR applications into strategic and tactical decision levels. This taxonomy provides a clear lens for analyzing research gaps. The focus at the strategic level lies in designing long-term system configurations – optimizing facility locations, capacities, waste flows, and technology portfolios under economic, environmental, and policy constraints. Decide the structure and long-term capacity of the system (generation → collection interface → transfer → treatment/recovery → disposal), typically via fixed-charge siting and multi-period expansion choices under multi-objective trade-offs. Surveys covering these decisions and methods include strategic/tactical levels OR in MSWM and integrated MSWM with sustainability framing (Asefi et al., 2020; Ghiani et al., 2014). Tactical level problems in MSWM involve designing medium-term policies and templates that bridge strategic infrastructure and day-to-day operations, including stable service districts, visit calendars/frequencies, fleet mix and shift templates, and assignments to depots/transfer/treatment (Beliën et al., 2014; Cortinhal et al., 2016; Ghiani et al., 2014). At the operational level, decision-making translates strategic and tactical level plans into the daily execution of collection services. This layer involves assigning stops to vehicles and crews, and scheduling trips and also unloads at transfer or treatment facilities, coordinating selective streams, and responding in (near) real time to traffic, equipment failures, or overflow events. It bridges long-term system design with day-to-day logistics, ensuring that municipal solid waste is collected efficiently, safely, and in accordance with service-level agreements (Asefi et al., 2020; Beliën et al., 2014; Ghiani et al., 2014). The taxonomy of representative OR problem areas in MSWM is presented in Table 1.

Table 1. *Representative OR problem areas in Municipal Solid Waste Management*

OR problem area	Corresponding MSWM task	Primary objective(s)	Representative OR models / techniques	Exemplary works
Facility Siting / Location–Allocation	Strategic-level planning of landfills, transfer stations, and treatment facilities	Minimize investment and transport costs; ensure service coverage; reduce environmental impact.	MIP; network design; decomposition approaches	Ghiani et al. (2014); Koushik et al. (2018, 2020)
Districting / Sectorization	Tactical-level partitioning of service areas into compact, contiguous, and balanced sectors	Minimize workload imbalance and travel cost; ensure compactness and contiguity	Multi-objective MIP; local search; matheuristics; GIS-assisted clustering	Billa et al. (2014); Cortinhal et al. (2016); Ghiani et al. (2014); Hemidat et al. (2017); Singh and Behera (2019)
Periodic Routing / Frequency Setting (PVRP)	Tactical-level scheduling of periodic waste collection by zone or waste stream	Minimize service cost and overflow risk; maintain reliability	Multi-period VRP formulations; metaheuristics (GA, ALNS, VNS)	Asefi et al. (2020); Beliën et al. (2014); Tirkolaee et al. (2018)

Table 1 cont.

OR problem area	Corresponding MSWM task	Primary objective(s)	Representative OR models / techniques	Exemplary works
Vehicle Routing (VRP)	Tactical/ operational level design of daily collection routes for vehicle fleets	Minimize total travel time, cost, and emissions while balancing workload	Exact MILP; metaheuristics (GA, SA, GRASP, ACO); hybrid GIS-based solvers	Beliën et al. (2014); Benjamin & Beasley (2010); Nuortio et al. (2006)
Routing with Intermediate Facilities (VRPIF)	Operational-level routing, including unloading trips to transfer/sorting stations	Minimize route time and unloading cost; respect facility windows and capacities	Multi-depot VRP; decomposition; heuristic-MIP hybrids	Benjamin & Beasley (2010); Ghiani et al. (2014)
Selective / Multi-Compartment Collection	Operational-level design of segregated or multi-stream collection	Minimize total distance and contamination; ensure vehicle-stream compatibility	MIP; rich VRP constraints; heuristic search	Goulart Coelho et al. (2017); Tirkolaee et al. (2018)
Fleet Sizing and Composition	Tactical-level determination of fleet size, type, and allocation to depots	Minimize investment and operating cost; match service frequency and workload	MILP; multi-period optimization; cost-based fleet allocation	Ghiani et al. (2014); Koushik et al. (2020); Rabbani et al. (2016);
Integrated Supply Chain / Network Optimization	System-level coordination of collection, transport, treatment, and disposal	Minimize total system cost; improve recycling and resource recovery efficiency	Multi-objective mathematical programming; multi-period flow models	Asefi et al. (2020); Goulart Coelho et al. (2017)
Uncertainty and Robustness in Operations	Operational-level planning under uncertain waste generation and travel times	Improve reliability; minimize overflow and overtime risks	Fuzzy optimization; stochastic programming; simheuristics	Asefi et al. (2020); Beigl et al. (2008); Tirkolaee et al. (2020)
Simulation for Policy and Operational-level Evaluation	Evaluation of new collection policies or recycling programs	Assess service quality, costs, and environmental outcomes	Discrete-event and continuous-discrete simulation frameworks	Antmann et al. (2013); Asefi et al. (2020)

As summarized in Table 1, the body of research demonstrates a clear methodological stratification. Strategic-level models remain dominated by mixed-integer formulations for long-term infrastructure and technology choices. In contrast, tactical-level models increasingly combine multi-objective optimization with matheuristics to balance efficiency, workload, and environmental criteria. Operational-level models, in turn, feature the most mature algorithmic development, especially in rich vehicle routing and scheduling variants. This structure highlights both the progression of methodological sophistication across levels and the persistent gaps in cross-level integration.

2.1. Strategic level problems

Strategic-level decision-making in MSWM is dominated by optimization models that formalize long-term system configuration, facility development, and technology selection as complex mathematical programs. According to Ghiani et al. (2014) and Asefi et al. (2020), these canonical problems can be categorized into several classes, including facility location and capacity sizing, multi-period expansion planning, technology and process-network design, multi-commodity network optimization, and policy-oriented system design. A foundational work by Ghiani et al. (2014) categorized these problems as location-allocation, network design, and system expansion models, which are most frequently formulated as MILP. These formulations typically minimize total system cost – including transportation, operation, and investment – while satisfying service coverage and environmental regulations. Multi-objective extensions balance conflicting goals such as minimizing cost, maximizing recycling, and reducing emissions.

The facility location and capacity sizing problem – deciding where to site landfills, transfer stations, material recovery facilities, composting or anaerobic digestion plants, waste-to-energy units, and residual disposal facilities – is a foundational optimization challenge. It is most often modeled as a fixed-charge facility location or capacitated network design problem solved through MIP or MIQP (Tirkolaee et al., 2018). These formulations minimize total system costs, accounting for capital investment, transportation, and operation, subject to constraints on facility capacity, siting restrictions, and service coverage. Multi-objective variants add diversion rates, greenhouse gas (GHG) emissions, and equity metrics as objectives. Cunha and Caixeta Filho (2002) advanced this line of research through a nonlinear goal programming model that simultaneously optimized economic efficiency, environmental quality, and social acceptability – one of the earliest multi-criteria optimization approaches in MSWM.

Multi-period capacity expansion planning is another critical strategic-level problem, involving decisions on the timing and scale of facility development, landfill cell construction, and technology upgrades in response to growth and regulatory pressures. Tirkolaee et al. (2018) describe these as multi-stage MILP models, featuring binary variables for facility opening and continuous flow variables, which are often solved using decomposition or Lagrangian relaxation to address the large-scale complexity. Similarly, Koushik et al. (2018, 2020) optimized the placement and capacity of treatment, transfer, and disposal facilities over multiple planning periods, demonstrating that the inclusion of transfer stations reduced total costs and transport distances by more than 10%. Their comprehensive MILP framework integrated treatment, transport, and transfer station location to minimize total system cost while ensuring network balance.

The technology selection and process-network design problem focuses on determining the optimal mix of recycling, composting, thermal, and residual disposal technologies. These models, typically formulated as multi-objective MILPs (Asefi et al., 2020; Tirkolaee et al., 2018), incorporate mass-energy balance equations to represent the yields of material and energy recovery. Studies such as those by Aliaga et al. (2021) have extended this approach to reverse logistics network optimization, where recovered materials are reintroduced into secondary markets. In parallel, multi-commodity network design models configure segregated waste streams (residual, recyclables, organics, bulky waste) across a regional network, minimizing costs or environmental impact while respecting contamination thresholds and market constraints (Tirkolaee et al., 2018). Regionalization and contracting models add another layer of realism by optimizing inter-municipal cooperation and shared infrastructure, often through cooperative cost-sharing or bilevel optimization structures.

Optimization at the strategic level also extends to policy design and regulatory planning, optimization models integrating policy instruments – such as pay-as-you-throw schemes, recycling incentives, and landfill taxes – into system-level design. These frameworks often use bi-level or scenario-based optimization to simulate the effects of policy on infrastructure investment and waste flows. At the same time, Asefi et al. (2020) emphasize the integration of energy and by-product recovery into planning models, coupling waste networks with power or heat grids to account for emission-revenue trade-offs. The complementary analyses by Goulart Coelho et al. (2017) highlight the use of multi-objective and game-theoretic formulations to examine the interactions among policy incentives, technology selection, and economic outcomes.

Across these classes, optimization objectives typically include minimizing total life-cycle cost, maximizing diversion or resource recovery rates, and minimizing GHG or pollutant emissions – often addressed through the ε-constraint or Pareto-front methods (Tirkolaee et al., 2018). Typical constraints capture facility and transport capacities, regulatory and environmental limits, contamination and quality specifications, labor availability, and spatial equity (e.g., maximum service distance). To handle uncertainty in waste generation, participation, material yields, energy prices, and regulation, models employ two-stage and multi-stage stochastic programming, robust optimization, and chance-constrained formulations, supplemented by simulation-based evaluations where analytical modeling is infeasible (Tirkolaee et al., 2018).

Empirical evidence further demonstrates the practical application of these optimization frameworks in real-world settings. Cabrera and Yabar (2018) developed a network-based spatial analysis framework for locating waste recovery facilities in Concepción, Chile, optimizing accessibility and transport efficiency through GIS-based network modeling. This finding underscores the trade-offs inherent in multi-objective optimization. Nevertheless, as Zeiss and Lefsrud (1996) and Vári (2000) emphasize, technically optimal solutions can face public opposition and governance barriers, revealing a persistent gap between mathematical optimality and social feasibility.

Strategic-level optimization in MSWM is grounded in MIP-based models for fixed-charge location, capacity expansion, and multi-objective network design, often supplemented by decomposition and stochastic extensions. These formulations have proven effective for system-level planning, technology selection, and policy evaluation. However, as Asefi et al. (2020) note, key gaps remain in incorporating uncertainty, dynamic capacity expansion, behavioral factors, and intertemporal policy feedback. Addressing these gaps through integrated, stochastic, and participatory optimization frameworks represents a crucial direction for future research in sustainable waste management planning.

2.2. Tactical level problems

At the tactical level of decision-making, OR provides analytical support for medium-term planning decisions that link long-term infrastructure design with short-term operational control. These optimization models address collection sectorization, routing, frequency planning, fleet allocation, and transfer network coordination, all of which are subject to resource, regulatory, and spatial constraints. This layer bridges strategic-level planning and daily operations, defining how available resources are organized to ensure continuous and efficient service delivery. As noted by Beliën et al. (2014), and Ghiani et al. (2014) tactical-level optimization in MSWM determines the configuration of collection districts, service frequencies, fleet composition, and depot assignments while balancing economic efficiency, environmental performance, and workload distribution.

A foundational tactical-level problem is districting or sectorization, in which municipalities are divided into compact, contiguous service zones that balance workloads among collection crews. Cortinhal et al. (2016) developed a sectoring-routing heuristic that jointly optimizes district boundaries and route design to achieve compactness and workload equity. Similarly, Kallel et al. (2016) integrated GIS tools into sectoring and routing optimization, demonstrating how geospatial data supports balanced and feasible collection plans. Huang and Lin (2015) extended this framework by incorporating social and policy constraints such as street access and collection time restrictions, demonstrating how tactical-level planning can reflect local regulations. Araiza-Aguilar et al. (2021) and Majid et al. (2021) proposed one of the early GIS-assisted heuristic approaches that incorporated vehicle accessibility into districting design, illustrating the role of spatial modeling in enhancing real-world feasibility. According to Ghiani et al. (2014), such problems are typically formulated as multi-objective MIP problems or solved with matheuristics, where cost minimization, travel-time balance, and compactness compete as key objectives. Reviews by Beliën et al. (2014) confirm that decomposition and local search techniques dominate this field due to the high combinatorial complexity of maintaining contiguity and balance constraints.

Tactical-level models also cover container allocation and vehicle coordination, which link strategic-level siting with operational-level routing. Mahéo et al. (2020) proposed a Benders decomposition model that integrates bin placement with route optimization, bridging long-term infrastructure design with tactical-level service planning. Likewise, Aliahmadi et al. (2020) introduced a fuzzy optimization approach for capacitated node-routing problems with multiple tours, embedding uncertainty in waste volumes – a rare example of explicit tactical-level uncertainty modeling. Container placement and sizing models, reviewed by Asefi et al. (2020) and Ghiani et al. (2014), determine the optimal number, type, and location of bins using integer programming, subject to accessibility constraints, contamination thresholds, and vehicle-container compatibility. These problems form a closed tactical-level decision loop that directly interacts with routing and frequency-setting tasks. In selective or segregated collection systems, additional complexity arises from waste-stream compatibility: Tirkolaee et al. (2018) and Goulart Coelho et al. (2017) modeled multi-commodity vehicle routing with compatibility matrices that account for multi-compartment vehicles and differentiated waste flows.

A related and long-studied tactical-level problem is periodic collection and frequency setting, often formalized as the Periodic Vehicle Routing Problem (PVRP). Beliën et al. (2014) and Asefi et al. (2020) describe how these formulations determine optimal day-of-week or seasonal schedules to minimize overflow risk while maintaining service reliability. Such models capture both routing and scheduling decisions and are frequently solved using metaheuristics – notably GA, Adaptive Large Neighborhood Search (ALNS), and Variable Neighborhood Search (VNS). Tirkolaee et al. (2018) extended the PVRP framework to multi-period and multi-objective MIPs, including environmental and capacity constraints, while Lei et al. (2020) introduced a discrete-continuous hybrid approach for recycling collection that captures tactical-level trade-offs between service intervals and processing coordination. Delgado-Antequera et al. (2020) and López-Sánchez et al. (2018) further developed multi-objective models, solved using GRASP-Variable Neighborhood Descent (VND) algorithm and iterated greedy heuristics, that simultaneously optimize cost, workload balance, and emissions.

The allocation of service zones to depots and transfer stations represents another canonical tactical-level issue. As Ghiani et al. (2014) note, this can be expressed as a Multi-Depot Vehicle Routing Problem (MDVRP) in which subareas are assigned to facilities subject to capacity, haul distance, and time-window constraints. Koushik et al. (2018, 2020) extended this logic in integrated MILP frameworks that combine depot assignment, fleet sizing, and transfer station utilization, demonstrating that optimized depot allocation can reduce system costs and travel distances by over 10%.

Tactical-level OR has also addressed heterogeneous fleet allocation and multi-compartment vehicle routing, especially under selective collection regimes. Rabbani et al. (2016) developed a hybrid GA to optimize heterogeneous fleet routing with multiple compartments for recyclable and residual waste. Assaf and Saleh (2017) employed GA-based optimization to adapt fleet routes to terrain and access limitations, whereas Das and Bhattacharyya (2015) calibrated deterministic fleet-route models for Indian cities to minimize collection and transfer costs. These works collectively demonstrate the diversity of tactical fleet planning approaches.

The literature also documents growing attention to multi-objective and stochastic tactical-level planning. Marković et al. (2019) and Tirkolaee et al. (2020) incorporated stochastic demand and fuzzy travel times into routing formulations. In contrast, Asefi et al. (2020) reviewed hybrid frameworks that combine MIP formulations with simulation or metaheuristics to manage uncertainty. Delgado-Antequera et al. (2020) introduced bi-objective optimization for cost-equity trade-offs, and Ghiani et al. (2014) emphasized workload balance as a key equity-based constraint.

Recent research trends have led to a shift in tactical-level models toward integrated and sustainability-oriented planning. Koushik et al. (2018) and Lei et al. 2020) incorporated recycling, energy recovery, and emissions into multi-objective frameworks, transforming traditional cost-based optimization into sustainability-driven decision-making. Similarly, Mojtahedi et al. (2021) and Asefi et al. (2020) linked routing and fleet planning with smart-city infrastructures, reflecting the increasing digitalization of tactical management.

Typical objectives of tactical-level models include minimizing total service cost (vehicle-hours, distance, fuel use), balancing crew workloads, and reducing environmental externalities such as emissions and noise (Beliën et al., 2014; Cortinhal et al., 2016; Ghiani et al., 2014). Typical constraints address compactness, service coverage, vehicle-waste compatibility, working hours, and depot capacities. Multi-objective trade-offs are frequently handled using ε-constraint or weighted-sum approaches (Tirkolaee et al., 2018). Simulation – especially with discrete-event and hybrid continuous-discrete models – is often used to test proposed collection policies and recycling initiatives before implementation (Antmann et al., 2013; Asefi et al., 2020).

Despite this methodological progress, the treatment of uncertainty remains a persistent gap at the tactical level. While operational-level studies frequently employ fuzzy and stochastic formulations, few works have applied these methods to tactical-scale models (Asefi et al., 2020; Tirkolaee et al., 2020). Beigl et al. (2008) emphasized that forecast uncertainty in waste generation and participation rates can substantially affect tactical-level planning, yet most studies continue to assume deterministic inputs.

Literature published between 2000 and 2021 reveals a clear evolution from deterministic routing and fleet sizing toward multi-objective, uncertain, and integrated tactical-level planning that accounts for environmental and operational variability. Nevertheless, as Ghiani et al. (2014) and Asefi et al. (2020) emphasize, the full integration of uncertainty and cross-level coupling across the tactical, strategic, and operational layers remains underdeveloped. Addressing these gaps requires end-to-end stochastic optimization frameworks that integrate tactical-level decisions on routing, sectorization, and fleet renewal with long-term sustainability and policy objectives.

2.3. Operational level problems

At the operational level, decision-making transforms strategic and tactical level plans into daily waste collection activities, enabling the design of efficient, reliable, and cost-effective services. This stage includes assigning stops to vehicles and crews, scheduling trips and unloads at transfer facilities, coordinating selective streams, and responding to traffic conditions or container overflow (Asefi et al., 2020; Beliën et al., 2014; Ghiani et al., 2014).

The VRP and its variants are the dominant operational-level formulations in the waste management literature. Foundational contributions, such as those by

Nuortio et al. (2006) and Benjamin & Beasley (2010), applied metaheuristics, including genetic algorithms, simulated annealing, and adaptive large neighborhood searches, to optimize collection routes for heterogeneous fleets and multiple depots. These models were later extended into rich VRPs that incorporate multiple trips, intermediate unloading at transfer stations, and working time limits (Beliën et al., 2014; Ghiani et al., 2014). In practice, these formulations capture the complex interplay between route duration, facility accessibility, and vehicle capacity.

Operational-level problems with intermediate unloading are modeled as the Vehicle Routing Problems with Intermediate Facilities (VRPIF). These formulations schedule unloading trips at transfer or treatment facilities within the daily tour, synchronizing route timing with facility hours and vehicle capacity resets (Benjamin & Beasley, 2010; Ghiani et al., 2014). For selective or multi-compartment collection, where multiple waste streams are collected concurrently, integer programming is used to encode compatibility rules between waste types, compartments, and facilities (Goulart Coelho et al., 2017; Koushik et al., 2018; Rabbani et al., 2016). These models improve route efficiency and compliance with separation requirements while minimizing total distance and operating time.

In arc-routing models, where waste is collected along street segments, capacity and uncertainty are jointly addressed. Tirkolaee et al. (2018) developed a robust periodic capacitated arc routing problem incorporating driver working hours and stochastic demand. Their hybrid ant colony optimization and simulated annealing approach demonstrated that metaheuristics can effectively handle large, uncertain networks, which are typical of municipal collection systems. Similar formulations have been used to balance workload, fuel use, and emissions under constrained shift durations (Tirkolaee et al. 2018, 2020).

Containerized and underground systems have introduced inventory-routing logic into operational-level planning. In such cases, route optimization depends on predicted container fill levels and overflow risk, which are often addressed through heuristics and short-term forecasting (Beliën et al., 2014; Faccio et al., 2011). Other models focus on appointment-based bulky waste collection, typically expressed as VRP with Time Windows variants with heterogeneous service and buffer times to account for schedule uncertainty (Ghiani et al., 2014). Crew assignment and shift feasibility are modeled as resource constraints within routing formulations to ensure compliance with labor and safety regulations (Benjamin & Beasley, 2010; Cortinhal et al., 2016).

Operational-level models typically pursue multi-objective optimization, aiming to minimize service costs and fuel consumption while balancing workload and reducing environmental externalities (Cortinhal et al., 2016; Ghiani et al., 2014). Constraints capture vehicle capacities, time windows, unloading cycles, stream compatibility, and accessibility restrictions (Beliën et al., 2014; Rabbani et al., 2016). Exact MIP is typically feasible only for structured cases, while city-scale problems rely on metaheuristics such as ALNS, GA, GRASP, ACO, and VNS (Benjamin & Beasley, 2010; Tirkolaee et al., 2018).

Simulation methods are increasingly used to evaluate operational policies before they are implemented. Antmann et al. (2013) employed continuous-discrete simulation to test daily and weekly plans, while Johansson (2006) and Ramdhani et al. (2018)

demonstrated real-time rescheduling of waste collection vehicles based on traffic updates. Such models provide insights into system reliability and capacity utilization, complementing optimization-based planning.

Digital and data-driven operations have emerged as a bridge between classical OR and real-time decision-making. Faccio et al. (2011) proposed a multi-objective model that integrates real-time traceability data into routing decisions, while Billa et al. (2014), Hemidat et al. (2017), and Singh & Behera (2019) demonstrated the use of GIS-based optimization for routing under urban accessibility constraints. As reviewed by Asefi et al. (2020), most digital applications framed sensor-driven collection as dynamic VRP or Inventory-Routing Problems, with optimization embedded within feedback control or simulation loops. VRP-based optimization, metaheuristic solution strategies, and increasing integration of simulation and digital monitoring characterize operational-level decision-making in MSWM. Despite this progress, treatment of uncertainty remains limited, and links to tactical and strategic layers are often unidirectional. As noted by Ghiani et al. (2014) and Asefi et al. (2020), future research should focus on fully integrated, stochastic optimization frameworks that connect operational-level responsiveness with long-term system sustainability.

3. RESEARCH GAPS IN THE APPLICATION OF OPERATIONS RESEARCH TO MSWM

Despite significant methodological progress, the literature on OR tools for MSWM remains fragmented across decision levels and constrained in its treatment of uncertainty, sustainability, and data integration. Existing reviews emphasize that although many models address strategic, tactical, or operational level issues individually, few provide an integrated, system-wide perspective that links facility planning, sector design, and daily routing (Asefi et al., 2020; Ghiani et al., 2014; Goulart Coelho et al., 2017). Most formulations continue to rely on deterministic assumptions and static planning horizons, with limited capacity to represent the dynamic and uncertain behavior of real waste systems. As a result, system-level coordination among infrastructure siting, collection frequency, and routing remains a central research gap.

At the strategic level, optimization models typically focus on facility location, capacity, and technology mix, often formulated as MILP (Asefi et al., 2020; Ghiani et al., 2014). While these models capture cost and regulatory constraints, they rarely include explicit feedback from downstream routing and service performance. The decoupling between strategic and operational layers leads to cost estimates that do not fully account for transportation variability, congestion, or selective collection requirements. Few works integrate facility siting and technology selection with realistic routing submodels or stochastic demand conditions (Koushik et al. 2018, 2020). This indicates a methodological opportunity for multi-stage or decomposition-based models that link siting and capacity expansion with collection logistics under uncertainty.

At the tactical level, the literature highlights a dominance of deterministic formulations for districting, service frequency planning, and fleet allocation (Asefi et al., 2020; Beliën et al., 2014; Cortinhal et al., 2016). Although empirical evidence suggests that fluctuations in waste generation and participation impact service quality (Beigl et al., 2008), explicit stochastic or robust tactical-level models remain relatively uncommon. Chance-constrained or fuzzy optimization – frequently applied at the operational level in routing – has seldom been extended to tactical-level problems, such as sectorization or periodic service planning. This gap limits the adaptability of medium-term decisions to real-world demand and travel-time variability.

OR in MSWM has been dominated by routing optimization, especially VRPs and their extensions for time windows, multi-trips, or multiple depots (Benjamin & Beasley, 2010; Nuortio et al., 2006; Tirkolaee et al., 2018, 2020). However, even within this rich corpus, most studies focus on deterministic instances, while only a few consider stochastic travel times or uncertain waste quantities. Simheuristic approaches and fuzzy formulations were introduced to capture these effects (Tirkolaee et al., 2020). However, large-scale applications integrating stochastic routing with upstream tactical or strategic level modules were still absent before 2021. Queueing and synchronization at transfer facilities were generally simplified, despite their importance for operational feasibility (Ghiani et al., 2014).

A recurring challenge across levels is the limited integration of sustainability and equity objectives. Multi-objective models are well established, yet most remain focused on economic and environmental trade-offs, with few incorporating social or fairness constraints (Asefi et al., 2020; Goulart Coelho et al., 2017). Workload balance is reflected in routing formulations (Cortinhal et al., 2016), but explicit environmental justice considerations – such as equitable access to services or reduction of exposure – are rarely formalized. Moreover, uncertainty is rarely considered in sustainability-oriented optimization, thereby reducing the robustness of long-term planning outcomes.

Another structural limitation concerns the reliance on static and scenario-based optimization. Multi-period frameworks exist, but they remain discrete and non-adaptive Digital and IoT-based approaches – such as GIS-assisted routing and fill-level monitoring – have shown potential for dynamic planning (Billa et al., 2014; Faccio et al., 2011; Hemidat et al., 2017; Johansson, 2006; Karadimas & Loumos, 2008; Ramdhani et al., 2018; Singh & Behera, 2019), yet hitherto implementations were largely prototype-scale. Most systems lacked the data infrastructure and standardization required for real-time re-optimization, reflecting a gap between methodological capability and technological readiness.

A foundational obstacle underpinning these issues are data bottlenecks. As Beigl et al. (2008) observed, waste composition and generation rates vary significantly across regions, which limits the transferability of models and the comparability of analysis. Data scarcity also hinders the development of standardized stochastic benchmarks for routing and facility planning. While deterministic routing benchmarks are well established (Benjamin & Beasley, 2010; Nuortio et al., 2006), open datasets incorporating time-dependent speeds, uncertain setups, or facility constraints are still lacking. Without such benchmarks, assessing the performance of stochastic and simulation-based optimization approaches remains challenging.

Critical thematic gaps persist in linking OR models to emerging challenges and transitions. Studies rarely integrate waste quality and market volatility into tactical or strategic level optimization, despite their significant impact on system costs (Goulart Coelho et al., 2017; Koushik et al., 2018). Similarly, hitherto, research has provided little insight into fleet electrification or resilience to shocks such as pandemics or extreme weather events, although these factors are increasingly shaping municipal logistics (Asefi et al., 2020; Tirkolaee et al., 2020). Operational disruptions and dynamic rerouting were discussed conceptually but seldom modeled quantitatively within integrated frameworks (see Table 2).

Table 2. *Identified research gaps and future directions*

Research gap	Substantive issue	Supporting evidence	Proposed future research direction
Global pandemic and shock resilience	Lack of comprehensive OR frameworks for managing extreme events that disrupt waste generation, composition, and logistics (e.g., COVID-19)	Asefi et al. (2020); Tirkolaee et al. (2020)	Develop adaptable, resilient optimization models capable of handling sudden changes in waste streams, medical waste surges, and service interruptions through multi-stage and robust formulations
Behavioral integration deficit	Limited modeling of human attitudes, participation rates, and community behavior in optimization; socio-behavioral dimensions treated qualitatively, not mathematically	Beigl et al. (2008); Ghiani et al. (2014)	Combine OR with behavioral modeling by embedding empirical participation data or behavioral response functions into tactical and strategic-level optimization frameworks
Data-driven bottleneck	The persistent lack of standardized, high-resolution, and reliable data on waste generation and composition hinders the transferability and validation of models	Asefi et al. (2020); Beigl et al. (2008)	Develop standardized data collection protocols, interoperable databases, and cost-effective sensor networks; integrate ML-based forecasting into OR models to close the data-model gap
Static vs. dynamic optimization	Over-reliance on static, scenario-based optimization that cannot adapt to real-time fluctuations in waste generation and traffic conditions	Faccio et al. (2011) Ghiani et al. (2014); Johansson (2006); Ramdhani et al. (2018)	Advance dynamic, IoT-enabled optimization and simheuristic models for adaptive routing, load balancing, and overflow prevention under uncertainty

Table 2 cont.

Research gap	Substantive issue	Supporting evidence	Proposed future research direction
Lack of integrated system-wide models	Strategic, tactical, and operational-level decisions are modeled separately, resulting in inconsistent system-level solutions	Asefi et al. (2020); Beliën et al. (2014); Ghiani et al. (2014).	Formulate hierarchical or decomposed models that link siting, capacity, and technology mix with districting, fleet planning, and routing using stochastic or multi-stage optimization
Limited uncertainty and robustness treatment	Deterministic assumptions predominate in tactical and strategic-level models, despite the known variability in waste generation and travel times	Beigl et al. (2008); Tirkolaee et al. (2018, 2020)	Extend robust and stochastic programming approaches to tactical and multi-period planning, applying chance constraints to optimize overflow and service reliability
Weak sustainability and equity integration	Environmental and social dimensions are often reported post-hoc rather than embedded in optimization objectives or constraints	Asefi et al. (2020); Ghiani et al. (2014); Goulart Coelho et al. (2017)	Develop multi-objective models explicitly co-optimizing cost, GHG emissions, and service equity using Pareto or ε-constraint methods under uncertainty
Simplified facility and queue representation	Intermediate facility capacities, congestion, and synchronization effects are seldom modeled, biasing routing feasibility and cost estimation	Benjamin & Beasley (2010); Ghiani et al. (2014)	Integrate queueing or simulation components within VRP with intermediate facilities (VRPIF) to capture stochastic unloading and facility interactions
Limited coupling between collection and processing	Models treat collection and treatment as independent subsystems, ignoring contamination, recovery yields, and market volatility	Goulart Coelho et al. (2017); Koushik et al. (2018, 2020)	Develop multi-commodity network models linking collection strategies to processing performance and economic value under uncertain market conditions
Fleet transition and decarbonization gaps	Few studies address the integration of electrification or alternative-fuel fleet routing into infrastructure planning	Asefi et al. (2020); Ghiani et al. (2014)	Extend vehicle-routing models to incorporate charging/refueling constraints, as well as the co-optimization of depot siting, emission reduction, and operational efficiency

Table 2 cont.

Research gap	Substantive issue	Supporting evidence	Proposed future research direction
Limited use of simulation-optimization beyond operations	Simulation is primarily used to evaluate routing performance rather than to optimize decisions at higher levels of abstraction	Asefi et al. (2020); Ghiani et al. (2014)	Combine discrete-event or system dynamics simulation with optimization to evaluate policy and planning alternatives under uncertainty
Absence of standardized benchmarks and open data for stochastic models	Existing benchmark sets cover only deterministic routing; no open datasets for uncertain generation or time-dependent networks	Ghiani et al. (2014); Nuortio et al. (2006)	Establish open, stochastic benchmark datasets and uncertainty scenarios to facilitate comparison and reproducibility of OR methods in MSWM

The state of research reveals several persistent limitations. OR applications in MSWM remain largely fragmented by decision level, constrained by deterministic assumptions, and weakly coupled to sustainability and social objectives. The field still lacks end-to-end stochastic and robust optimization frameworks that bridge infrastructure planning, service design, and routing operations under uncertainty. Progress toward real-time, data-driven decision support was evident but incomplete, constrained by the availability and standardization of waste data. Addressing these gaps – through integrated, uncertainty-aware, and sustainability-oriented modeling – represents a clear direction for future OR research in municipal waste management.

4. CONCLUSION

This review set out to identify and articulate the principal research gaps and limitations in the application of OR to MSWM as of 2021. Guided by three research questions, the analysis has provided a structured understanding of how decision problems have been modeled, which methodological families have dominated, and where the integration of uncertainty, sustainability, and multi-level decision-making remains incomplete.

Addressing RQ1, the classification of MSWM decision problems reveals that OR methods have been extensively applied across all three planning horizons – strategic, tactical, and operational levels. Strategic-level studies have focused primarily on facility siting, capacity expansion, and technology mix decisions, typically formulated as mixed-integer programming models. Tactical-level models have addressed routing, sectorization, fleet composition, and collection frequency, while OR has concentrated on rich vehicle routing problems and daily scheduling under detailed logistical constraints. Over time, the field has evolved from simple, cost-oriented formulations to multi-objective, sustainability-aware models that integrate environmental and service-related performance indicators.

In response to RQ2, the literature emphasizes optimization and metaheuristics, with limited but growing contributions from simulation and hybrid simulation-

-optimization frameworks. While deterministic formulations remain prevalent, stochastic, fuzzy, and robust optimization approaches have been increasingly employed to capture uncertainty in waste generation, participation rates, and travel conditions. However, uncertainty treatment remains mainly confined to operational-level models, leaving higher-level decisions – such as network design and fleet planning – dominated by static and scenario-based approaches. The field's progress in methodological diversity is thus substantial but uneven across decision layers.

Concerning RQ3, methodological integration across decision levels remains an important but underdeveloped frontier. Although several studies recognize the interdependence among strategic, tactical, and operational-level planning, few offer comprehensive frameworks that link facility location, sectoring, and routing decisions under shared stochastic conditions. Most existing models operate in isolation, which limits their ability to represent real-world system interactions and dynamic feedback accurately. Similarly, multi-objective integration – balancing cost, emissions, and equity – has advanced conceptually but is rarely implemented in unified, uncertainty-aware formulations.

Despite these advances, three cross-cutting limitations continue to constrain the field. First, the behavioral integration deficit remains a fundamental barrier. The human and social dimensions of waste generation and participation – despite being acknowledged as critical – have yet to be formally embedded within quantitative OR models. Second, the data-driven bottleneck persists: the lack of standardized, high-quality datasets hinders both model calibration and the adoption of AI- and ML-based predictive approaches. Finally, the transition from static to dynamic optimization represents a significant, yet unfulfilled, opportunity. While IoT technologies promise real-time monitoring and adaptive decision-making, implementation remains limited by infrastructure and cost barriers.

In light of the three guiding research questions, the review reveals that, although strategic, tactical, and operational decision-making problems in MSWM have been widely studied, the corresponding OR models remain methodologically fragmented across these levels. Deterministic formulations continue to dominate, and uncertainty, sustainability criteria, and cross-level integration are addressed unevenly. The review period up to 2021 also reveals growing interest in simulation-based evaluation, yet real-time adaptive optimization remains limited by data availability and interoperability across systems. Future work should therefore prioritize (1) integrated, multilevel decision frameworks, (2) explicit modeling of uncertainty and resilience, and (3) data-driven, dynamically updating optimization supported by sensor and digital monitoring systems. Such developments would enable OR methods to support practical, scalable, and sustainability-aligned MSWM planning and operations more fully.

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