



Balancing efficiency and sustainability in waste collection fleet operations: A fleet optimization and electrification perspective in a real case study

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ABSTRACT

The optimization of municipal solid waste collection presents a dual challenge of improving operational efficiency while minimizing environmental impact. This study addresses these challenges by developing an optimized distribution plan incorporating sustainable development principles within a capacitated vehicle routing problem framework. This research addresses the gap in evaluating the operational cost and environmental impacts of MSW management, particularly focusing on optimizing fleet electrification and waste collection processes. This study aims to fill this gap by proposing an optimization model for waste collection, integrating fleet electrification to reduce greenhouse gas emissions and operational costs. In addition, the optimized fleet routes are utilized in this study to evaluate five electrification scenarios (20%–100% electrification) to analyze economic and environmental impacts using MATLAB. This research focuses on a case study in Narni, Italy, where ASM Terni S.p.A. manages waste collection operations as a multi-utility in Italy. Electrification scenarios show significant reductions in fuel costs and emissions, even exploiting a decision support system that optimally manage charging sessions of the Electric Vehicles after the daily waste collection using available Charging Stations in the headquarters.

1. Introduction

The door-to-door (DTD) waste collection method has proven highly effective in achieving a significant rate of waste separation and is meticulously designed with ergonomic considerations to ensure the health and safety of the waste collection staff (Botti et al., 2020). Each waste type requires a different collection time. For example, organic waste, being low in volume, allows operators to complete their tasks early, using the remaining time to start collecting higher-volume types such as paper or plastic, which are usually completed by the following day. One of the significant challenges in practical operations is ensuring route familiarity, as operators need several weeks or months to efficiently manage tasks on a specific route. Reassigning operators due to unexpected circumstances, like a colleague's absence, often leads to decreased service quality. Furthermore, workers on the most demanding routes tend to suffer from injuries and fatigue due to varying route characteristics such as the number of bins and distances covered.

The COVID-19 pandemic has exacerbated solid waste management challenges globally (Haque et al.). While food waste generation declined due to increased environmental awareness (Burlea-Schiopoiu

et al., 2021), the use of Personal Protective Equipment (PPE) such as face masks and gloves surged, significantly increasing solid waste production (Haji et al., 2020). In response, municipalities have implemented contingency plans to improve waste collection efficiency, as improper waste management could contribute to virus transmission (World Health Organization, 2020). Recent studies have increasingly focused on reducing greenhouse gas emissions from logistic networks, integrating both economic costs and environmental benefits in the MSW collection process. To further address operational issues, waste collection vehicles have been equipped with navigational systems that display optimized routes and bin positions, enabling fleet managers to reduce manpower needs and fleet size. In addition, optimization techniques can enhance fleet management, vehicle allocation, and maintenance scheduling.

A key computational challenge in waste collection is solving the capacitated routing problem, where a fleet of vehicles with specific load capacities must visit designated locations and return to the depot. Finding exact solutions for large-scale problems is often impractical, so heuristic and metaheuristic methods have been developed to find effective solutions in a reasonable timeframe. Meanwhile, integrating EVs into waste collection fleets can significantly reduce CO₂ emissions and pollutants in urban areas by using greener energy sources such as

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Acronyms		
CS	Charging Station	
CVRP	Capacitated Vehicle Routing Problem	
DTD	Door-to-Door	
ELRP	Electric Location Routing Problem	
EV	Electric Vehicle	
GHG	Green House Gas	
GIS	Geographic Information System	
GLS	Guided Local Search	
IoT	Internet of Things	
MSW	Municipal Solid Waste	
MSWM	Municipal Solid Waste Management	
OSRM	Open-Source Routing Machine	
PPE	Personal Protective Equipment	
TWL	Threshold Waste Level	
V2G	Vehicle-to-Grid	
VRP	Vehicle Routing Problem	
Sets and indices		
t	index of time, running from 1 to N_T , used as a subscript	
i	index of individual electric vehicles, running from 1 to N_{EV}	
		used as a subscript
		index of electric vehicle charging stations, running from 1 to N_{CS} , used as a subscript
Parameters		
N_T	total number of time periods	
N_{EV}	total number of electric vehicles	
N_{CS}	total number of charging stations	
$EV R_{0,i}$	random initial energy range for the electric vehicle i at timestamp t_0	
$EV R_i[t]$	available range (energy level) of vehicle i at time t	
$EV R_{\max}$	maximum range of the electric vehicles	
$EV R_{\min}$	minimum allowable range for the electric vehicles	
$DT_i[t]$	distance travelled by vehicle i at time t	
$EV S_i[t]$	charging status of vehicle i at time t (1 if charging, 0 if not charging)	
Variables		
$EV_{bin,i}[t]$	binary variable that determines if vehicle i is being considered for charging at time t (0 or 1)	
$EV R_i[t-1]$	Residual energy available from the previous time step for vehicle i	

solar power. This shift decreases reliance on fossil fuels and enhances energy infrastructure resilience, supporting broader clean energy and climate change initiatives.

This paper aims to optimize waste collection and transportation operations sustainably, with a focus on a real-world case study in Narni, Italy. This research represents a novel approach to examining similar scenarios, aiming to demonstrate the benefits of an optimized procedure on work efficiency and environmental sustainability. The study incorporates fleet electrification supported by existing charging stations at the depot, with adjustments to charging schedules across scenarios to optimize resource use and maintain operational readiness. The service analyzed in this case study is provided by ASM Terni, a multi-utility company that manages multiple public services, including electricity,

gas, water, and waste collection. ASM Terni operates a fleet of 28 vehicles across a diverse municipal area that includes a medieval city center, modern residential neighborhoods, industrial zones, and rural regions. Initially, a comprehensive evaluation was conducted, gathering data on district geography and customer bin locations, including historical data from ASM Terni. A distance matrix and duration matrix were then created to assess the distances and travel times between each pair of bins, including the depot. In the next phase of the research, the vehicle routing problem was tackled using OR-Tools, an open-source Python library developed by Google. This library employs Guided Local Search (GLS) to solve vehicle routing problems, flows, integer and linear programming, and constraint programming (<https://developers.google.com/optimization?hl=it>). The final outcome is an optimized route for

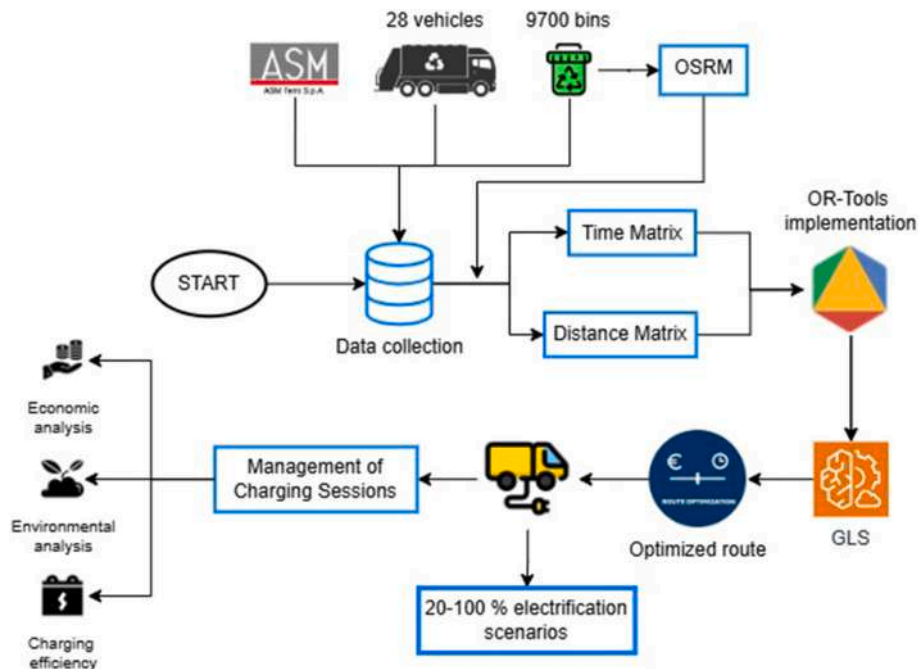


Fig. 1. – Graphically implemented flow chart in waste collection fleet/operation optimization.

each vehicle, specifying the sequence in which bins should be collected.

Additionally, the research investigates the electrification of the waste collection fleet and its scheduling, utilizing the available charging infrastructure at ASM Terni. The ultimate goal of this paper is to reduce operational costs, minimize energy consumption and GHG emissions, and optimize coordinated decisions in the waste collection and transportation process. The innovation of this study lies in its comprehensive route and fleet analysis and the development of a new operational methodology for waste collection electrification in this specific real-world context. This holistic approach aims to enhance the efficiency and sustainability of waste management practices, providing valuable insights for similar initiatives in other municipalities. Fig. 1 shows a graphical flow chart implemented in this work for waste collection fleet/operation optimization.

The structure of the paper is as follows: Section 2 reviews the literature on fleet optimization, vehicle routing problems (VRP), and electrification strategies, identifying research gaps. Section 3 outlines the methodology for optimizing charging sessions. Section 4 presents the case study, model assumptions, and scenarios. Section 5 analyzes the results of CVRP and electrification and Section 6 concludes the paper and suggests future research directions.

2. Literature review

2.1. Survey of fleet optimization methods

Recent studies have explored various aspects of solid waste collection management, including strategy design, collection and disposal methods, environmental impacts, and operational challenges (Das et al., 2021a). Efficient fleet management, particularly vehicle routing, plays a key role in reducing costs, mitigating environmental damage, and enhancing operational efficiency (Chen et al., 2020). Several optimization models have been developed to address these challenges. For instance, a model for optimizing solid medical waste collection focused on designing a sustainable transportation network (Babaei et al., 2021). Zaeimi and Rassafi emphasized reducing municipal costs and minimizing environmental impacts through optimized waste collection operations (Zaeimi et al., 2021). Similarly, Mahmuda Akhtar et al. (2017) introduced the Threshold Waste Level (TWL) concept to improve efficiency and reduce costs like fuel consumption and CO₂ emissions. Their follow-up study (Hannan et al., 2018) further optimized week-long scheduling, and M. Faccio et al. (2011) designed a multi-objective VRP model to reduce total distance, vehicle requirements, and environmental impact. Herold and Lee (2019) explored the effects of internal and external practices on carbon disclosure strategies in logistics companies. Moreover, in the context of fleet optimization during pandemic-related disruptions, Das et al. (2021) proposed a heuristic model integrating constraints from COVID-19 waste generation trends. Wang et al. (2022) explored data-driven fleet optimization strategies that incorporate real-time tracking and adaptive algorithms to respond to dynamic urban conditions. Building on these, recent efforts like Zhang et al. (2023) employ machine learning to enhance route prediction, considering socio-environmental constraints for municipal waste collection.

Optimization techniques are essential in overcoming planning challenges in waste management, focusing on minimizing costs, distance, time, and environmental impact. Das and Bhattacharyya (2015) proposed a heuristic model that reduced total travel distance by over 30% in waste collection and transportation. MSWM involves key activities like waste collection, separation, recovery, and scheduling. While significant progress has been made in developing efficient waste management strategies, the integration of smart city models for waste collection and separation remains limited. Pires et al. (2011) applied system analysis to develop waste management schemes for European Union (EU) countries, stressing the need for innovative strategies. Anagnostopoulos et al. (2015a) took it further by proposing a high-priority area waste

management solution using the Internet of Things (IoT), reducing service times and boosting operational efficiency in critical areas.

In the context of smart cities, Anagnostopoulos et al. (2015b) developed a robust routing algorithm utilizing IoT to deploy two types of trucks, significantly reducing operational costs. Massana et al. (2017) also explored strategies for smart cities by creating a model for short-term load forecasting in non-residential areas, promoting sustainability. With the advancement of smart technologies, smart waste bins are becoming increasingly common. Ramos et al. (2018) proposed a system that uses IoT sensors to monitor waste bin fill levels in real-time, managing the uncertainty and optimizing the waste collection process. They introduced a CVRP model to minimize the total distance travelled while maximizing the profit of waste collection operations.

The VRP remains a cornerstone in fleet optimization research. The inclusion of real-world variables such as time windows, vehicle capacity, and urban traffic conditions continues to shape the field. Recent extensions of VRP include dynamic modeling approaches that incorporate real-time data to optimize routing and scheduling. For example, Li et al. (2021) developed an adaptive VRP model incorporating real-time traffic conditions and environmental goals. Similarly, Chen et al. (2022) introduced an urban logistics model that integrates IoT-enabled waste bins to monitor collection needs dynamically.

Effective waste management involves not only the collection of waste but also identifying optimal transport and disposal sites. CVRP models have been a major focus for improving waste management efficiency. Akhtar et al. introduced a CVRP model designed to reduce the overall waste collection budget, incorporating the TWL concept to optimize bin numbers and reduce travel distances. Lozano et al. (2018) expanded on these ideas by applying IoT and an ambient intelligence-based heuristic algorithm to further enhance the efficiency of waste collection in smart cities. These studies highlight the crucial role of optimization and advanced technologies in addressing the challenges of modern waste management systems.

2.2. Existing studies on VRP

Waste collection and transportation is a key application of VRP, and numerous studies have addressed VRP within the context of MSWM. For example, Buhrkal et al. (2012) tackled the waste collection vehicle routing problem by incorporating time windows and worker lunch breaks into their model. They utilized a greedy algorithm to construct the initial solution, which was refined through an adaptive large neighborhood search using destroy and repair methods, demonstrating effectiveness in route optimization. Similarly, Hemmelmayr et al. (2013) applied dynamic programming for variable neighborhood search and insertion procedures to address waste collection node routing, further improving route efficiency.

Recent advancements have continued to refine VRPs for waste collection. Battaia and Dolgui (2022) developed a unified approach to capacitated VRPs, incorporating solid waste collection constraints to enhance practicality. Rezaei and Kian (2023) introduced a new meta-heuristic for mixed pickup and delivery VRPs, significantly improving municipal waste collection operations. Additionally, Yu et al. (2022) proposed a hybrid genetic algorithm for VRPs with time windows, optimizing route efficiency for urban waste collection operations.

The Vehicle Routing Problem has been extensively studied since its introduction in the 1960s, leading to the development of various solving methods, including exact, heuristic, and meta-heuristic approaches (De Armas et al., 2015). However, due to the inherent complexity of VRPs, exact methods often prove inefficient (Solomon, 1987). Several researchers have applied VRP to waste collection, with a focus on optimizing routes and minimizing travel distances. Delgado-Antequera et al. (Delgado-Antequera et al., 2020) emphasized travel distance as a key factor in route optimization for waste collection. Rızvanoğlu et al. (2020) used linear programming and Geographic Information System (GIS) analysis to optimize waste collection routes, demonstrating

significant improvements. Tirkolaee et al. (Zhao et al., 2016) developed a model incorporating time windows to prioritize hazardous waste collection from sites like medical centers and hospitals. Armas et al. (Babaei Tirkolaee et al., 2019) proposed a rich VRP model with customer priorities, solved using a heuristic algorithm. Wu et al. (2022) developed a bi-objective model for municipal solid waste collection that balances economic costs and environmental impact by optimizing fleet operations and emissions reduction. Tang et al. (2023) proposed an integrated model considering trade-offs between cost and carbon emissions for MSW management in urban areas, providing insights into sustainable policy design. These studies highlight the importance of optimizing waste collection routes to improve efficiency, reduce costs, and minimize environmental impact.

One of the most notable extensions of VRP is the Capacitated Vehicle Routing Problem (CVRP), which includes vehicle capacity constraints (Rocha Medina et al., 2011). Significant research has been conducted on CVRP, with Pelletier et al. (2019) proposing a two-phase heuristic method based on large neighborhood search, identifying new optimal solutions for the robust CVRP. Mathematical models and optimization algorithms for MSW collection continue to evolve. Akhtar et al. (2017) developed a modified backtracking search algorithm to optimize solid waste collection routes, achieving a more than 30% reduction in total travelled distance by minimizing route distance, fuel costs, and CO₂ emissions.

2.3. State-of-the-art in electrification strategies for fleets

Electric vehicles have emerged as a key approach for achieving sustainable development goals in waste collection operations. Electrifying solid waste collection vehicles is particularly advantageous because these vehicles operate on fixed routes over limited distances and return to their depot every night, enabling effective operation with relatively small batteries. This predictable operation pattern also simplifies route planning and charging scheduling, making it easier to integrate electric vehicles into existing waste collection systems without significant operational disruptions. Developing the infrastructure necessary to support EVs for daily municipal waste collection is crucial to reducing both costs and environmental impact, particularly during crises such as pandemic outbreaks. However, there has been limited research on the use of EVs for waste collection during such outbreaks.

Most studies on waste collection fleets focus on different objectives and constraints, generally using internal combustion engine vehicles to meet sustainability goals. Similar to other MSW collection operations, green objectives have become increasingly important in vehicle routing problems (Bektaş et al., 2019). However, unlike these studies, Erdinc et al. (2019) specifically investigated the use of EVs in waste collection. They initially analyzed the drivetrain dynamics of EVs and created an energy consumption formula, which was then integrated into a simplified model. Despite the extensive use of arc routing in urban management and the growing significance of EVs in transportation, few studies have explored EVs in the context of arc routing. Zuo et al. (Zuo et al., 2019) presented a mathematical model with a convex non-linear charging function. Yang and Sun (Yang and Sun, 2015) introduced the Electric Location Routing Problem (ELRP), determining optimal locations for battery swapping stations and routes for EVs. Arias et al. (Arias et al., 2018) examined the effects of charging stations and EV routing on power distribution systems using a mixed-integer non-linear model. Zhang et al. (Zhang et al., 2019) investigated the impact of stochastic demand on minimizing the total cost of stations and routing.

Recent literature reviews on EV energy consumption and route planning highlight numerous constraints affecting energy usage. Early studies incorporated battery constraints into the Dijkstra algorithm (Artmeier et al., 2010). Other extensions of EV route planning have focused on trip time, with studies such as (Chau et al., 2017) investigating the fastest feasible routes while minimizing total trip time. Further research has addressed recharging constraints. For example,

Song et al. (2023) proposed multi-layered optimization strategies for EV route planning, which integrate charging station distribution, grid impacts, and operational constraints. Their approach considers not only the spatial placement of charging infrastructure but also the temporal dynamics of grid demand and EV charging patterns, enabling optimized scheduling that minimizes both operational costs and grid strain. Moreover (Baum et al., 2017), studied partial recharging at stations using the concept of "state of charge." Research on EV fleet route optimization has been conducted, with techniques aimed at minimizing waiting times for EV taxi fleets (Dong et al., 2017). Factors such as geographical and temperature influences on energy consumption were also examined, helping to estimate optimal routes and durations (Lobo et al., 2019). Speed planning for fuel savings, traffic flow considerations, and dynamic traffic networks have been integrated into EV trajectory planning and charge navigation strategies (Hartmann and Funke, 2014). Alizadeh et al. (2014) addressed route selection, charging locations, dynamic location-based electricity pricing, and charge amounts under time-varying traffic conditions. In addition, studies (Ding et al., 2017) explored travel time, traffic conditions, energy consumption, and route length. Research in (Van et al., 2021) also discussed the impacts of personal driving behaviors and physical factors, such as traffic lights, road topology, and stop signs, on EV routing.

2.4. Research gap

The literature review shows that although several studies have examined MSWM in the context of a pandemic outbreak, some essential health aspects are neglected. Additionally, environmental pollution caused by road cleaning operations with trucks running on fossil fuels has not been adequately addressed in the literature. Furthermore, while electrification of vehicle fleets has been recognized as a key approach for sustainable development, the integration of EVs into MSWM operations, especially concerning optimized scheduling and charging, has not been fully explored. The main purpose of this paper is to obtain an optimal distribution plan that incorporates sustainable development principles in MSW collection, addressing gaps in operational cost efficiency and environmental impacts of waste collection. A CVRP model is developed to optimize MSW collection. This model will include considerations for the electrification of the fleet and the scheduling of charging to ensure the efficient use of EVs. Therefore, the literature review is composed of three parts: research on sustainable development in MSW collection, algorithms for the CVRP model, and fleet electrification, including optimal scheduling and charging infrastructure.

3. Methodology

The methodology that is proposed in this paper exploits existing tools for solving CVRP and an original decision support system for charging station. The methodology allows to assess the benefits of the optimized routes as well as the shift from traditional fleet to EV. The methodology is applicable assuming that all the coordinates of the bins are known and the collection time and distance is estimated, which is used to obtain vehicle routes in waste collection operation.

Time is the most critical constraint in this optimization process. The company must complete all operations within a standard business day, meaning each route should be finished by its respective vehicle within a defined time window. To model this realistically, an average stop time per customer for waste collection has been used, derived from data collected over several hundred stops. In practice, the company has observed that some types of waste, such as organic and glass, have shorter average stop times, while paper and plastic require longer. However, to streamline operations, the company uses the spare time on days dedicated to organic and glass collection to begin collecting the more time-consuming waste types, which are usually scheduled for the next day. Therefore, an average stop time across all waste types has been used for the model.

A preparatory step for the optimization involved the definition of a matrix that details the travel time between each possible pair of bin coordinates. This process was accomplished using the Open-Source Routing Machine (OSRM), which provided the travel time over the fastest route between each pair of locations under ideal traveling conditions (e.g., absence of traffic). The matrix also included the location of the depot, where trucks are parked and offload the collected waste.

Similarly, OSRM generated a distance matrix, where each entry corresponds to the length of the fastest route between locations, as reflected in the time matrix. Therefore, these distances represent the lengths of the fastest routes rather than the shortest ones. From a practical standpoint, the company is primarily focused on optimizing the procedure to reduce the total operation time. Consequently, the distance matrix is not directly involved in the optimization process but is instead used to calculate the lengths of the routes post-optimization.

The optimization of waste collection routes was performed using OR-Tools, a Python library developed by Google, which employs GLS to avoid local optima in large vehicle-routing problems. The objective function minimizes the total travel time and balances the workload among vehicles. The data model includes the time matrix, fleet size, vehicle capacities, and distance matrix. Advanced optimization algorithms were implemented in several steps: data acquisition and pre-processing, model construction, routing optimization, solution search, and result analysis. The CVRP model was built using OR-Tools, incorporating data such as duration and distance matrices and customer demands. The optimization process involves defining transit callbacks, adding a time dimension, and using heuristics and local search algorithms to refine solutions. The effectiveness of optimized routes is assessed by evaluating reductions in operational costs, travel time, fuel consumption, and CO₂ emissions. This approach aims to develop a robust and efficient solution for optimizing waste collection routes, enhancing sustainability and cost-effectiveness.

3.1. Optimizing charging sessions

The methodology includes an optimization model that identifies the optimal scheduling of the charging sessions. These parameters are necessary to ensure the accuracy and relevance of the analysis:

- Operational assumptions (i.e., maximum allowed duration, maximum number of charging sessions, location of the main depot),
- Travelled distance by the vehicle in the fleet,
- Battery capacity and estimated range and related consumption per unit of travelled distance,
- A minimum battery capacity that must be ensured by the decision support system (e.g., this value can be provided by the fleet manager based on range anxiety or minimum travelled distance),
- Load capacity,
- Knowledge of the State of Charge of the vehicles,
- Charging station peak power.

Finally, in order to make the comparison of the two fleets, emissions for the operation of each vehicle type should be collected, therefore the average emission for 1 kWh of absorbed energy should be taken into account.

The developed optimization model takes into account these parameters in order to optimally define the schedule of the charging sessions so that all the vehicles have always enough capacity for daily operation as well as minimizing the number of charging sessions in order to estimate which is the minimum required number of charging sessions. It was developed assuming that i) the model manages a fixed number of CS (N_{CS}) and EV (N_{EV}); ii) every day the available time for charging EV is enough to restore the EV range up to the full capacity; iii) as a consequence, the optimization model considers only daily variation of EV range (i.e., variable are daily sampled); iv) the output of the simulation is the binary variable EVS which defines for each EV (i) and for each day

(t) the EV status, namely if the EV is on charge EVS_i is equal to 1 otherwise, EVS_i is equal to 0; v) optimization is carried out assuming a fixed number of analyzed days (N_T).

The objective function, as defined by equation (1), prescribes that the total number of charging sessions for all electric vehicles (N_{EV}) across all time periods (N_T) has to be minimized. The constraints governing the optimization problem are defined by equations (2)–(5).

$$obj = \min \left(\sum_{t=1}^{N_T} \sum_{i=1}^{N_{EV}} EVS_i[t] \right) \quad (1)$$

$$EVR_i[t_0] = EVR_{0,i} \quad (2)$$

$$0 \leq \sum_{i=1}^{N_{EV}} EV_{bin,i} \leq N_{CS}, \forall t \quad (3)$$

$$EVR_i[t] = (EVR_i[t-1] - DT_i[t]) * (1 - EVS_i[t]) + EVR_{max} * EVS_i[t], \forall i, t > t_0 \quad (4)$$

$$EVR_i[t] > EVR_{min} \quad \forall i, t \quad (5)$$

Equation (2) defines the initialization of the model, namely, for the initial timestamp (t_0), the initial EV range (EVR) is defined ($EVR_{0,i}$); as an example, $EVR_{0,i}$ could be randomly defined. Equation (3) defines that the number of charging sessions cannot overcome the number of charging stations. In equation (4), the daily energy balance is defined; notably, the energy available EVR at the end of the present day t could be equal to the difference between the residual energy of the previous day and the energy consumed because of the travelled distance DT if the EV is not charged (i.e., EVS is equal to 0). If EVS is instead set equal to 1, the EV is charged; therefore, EVR reaches the full capacity EVR_{max} as was assumed in the formulated hypothesis at the beginning of this subsection. Equation (4) is applied to all the vehicles and all the analyzed timestamps. Finally, equation (5) ensures that the EVR is always greater than a minimum value EVR_{min} .

The model was implemented in MATLAB with the YALMIP library and using GUROBI as an optimizer. The output of the model is EVS , namely the envisioned status of the EV.

4. Case studies and Experimental setup

4.1. Case study

The developed methodology was applied to a real case study, namely the waste collection fleet for the city of Narni which is managed by ASM Terni S.p.A. This company operates as a multi-utility company in the municipality of Terni, located in the Umbria region of Italy. The company manages a range of services including electricity, gas, water, and waste collection. Fig. 2 illustrates the geographical position of the case study.

With respect to the waste management service, the company maintains a database containing the geographical coordinates of customers' waste bins and aims to design optimal routes for their fleet. Each vehicle, starting from the depot in the morning, is expected to service a specified number of customers and return to the depot by the end of the business day in the shortest possible time. The waste collection operations are conducted by a fleet of 143 vehicles, primarily powered by internal combustion engines and typically refueled at ASM headquarters (Bragatto et al., 2022).

For this case study, 28 vehicles from this fleet are actively engaged in waste collection within the Narni district, which includes about 9700 waste bins. Table 1 provides key characteristics of the waste collection bins based on historical data from the district.

A relevant constraint in this subset of routing problems is the capacity of the vehicles: each truck in the fleet has a defined capacity ranging from 2.5 to 10 m³. However, for this optimization model, it has

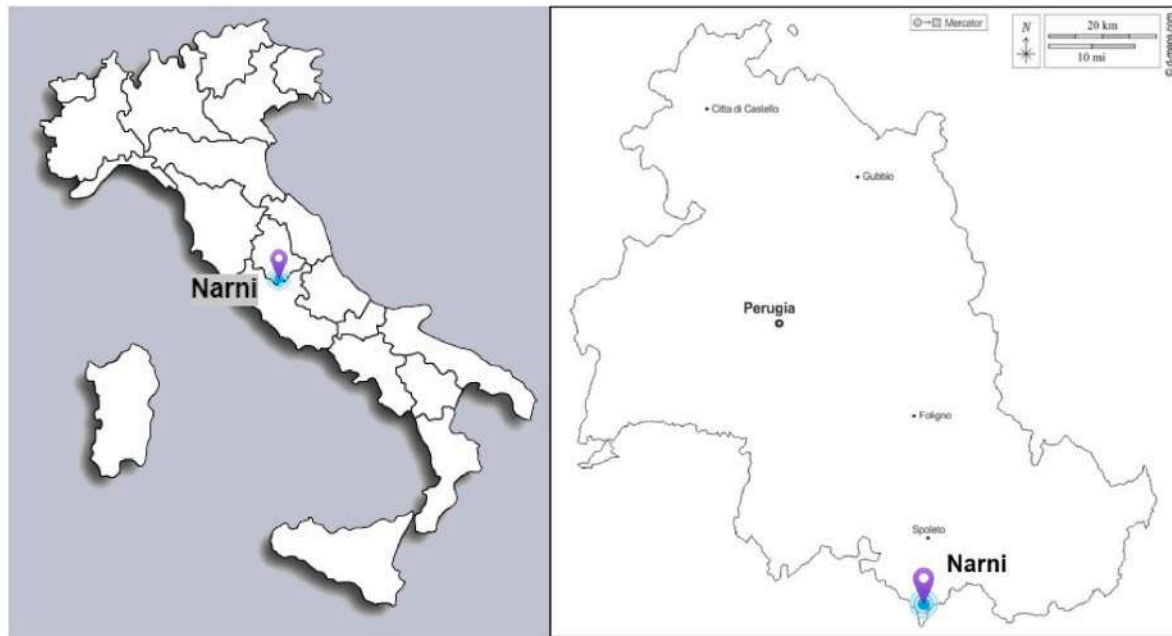


Fig. 2. – Geographical position of Narni, Umbria, Italy.

Table 1

– Bin characterization in the case study.

Bin type	Numbers	Size (m ³)
domestic users	6362	0.04
non-domestic users	1158	0.04
garages	269	0.08
canteen	383	0.06
farm buildings	23	0.10
Ruins	65	0.10
caditoie (drain)	913	0.12
Stalls	353	0.06
Baskets	97	0.12
waste battery containers	31	0.06
containers for expired medicines	8	0.06
collection centers	1	0.06
market area	1	0.06
parks	17	0.06
others	19	0.06
total points	9700	
dense area users	6101	
non-dense area users	1398	

been assumed the use of vehicles and bins with uniform capacities to streamline operations and ensure waste collection is completed within a specific time frame. The primary objective is to optimize routes and vehicle assignments to minimize operational costs, time, fuel consumption, and emissions. The analysis also assumes a diesel fuel cost of 1.90 € per liter and an emission rate of 2.4 kg of CO₂ per kilometer travelled. Fig. 3 illustrates the distribution of waste bins throughout the district.

Additionally, historical data is accessible through Arcoweb, a platform operated by Altares Company, which facilitates route monitoring and vehicle tracking for collection vehicles equipped with geolocation technology (<https://www.satservizi.org/chi-siamo/tecnologia-in-sat/>). ASM Terni already leverages real-time communication capabilities via this platform, enabling fleet visualization. This feature will be further explored in subsequent scientific articles. However, this study focuses on simulating a novel approach to route optimization, without considering historical vehicle travel data.

4.2. Model assumptions and simulated scenarios

The electric waste collection vehicles are assumed to have a battery capacity of 300 kWh, providing an estimated range of 300 km on a full charge. It is assumed that the load capacity of these electric vehicles is slightly reduced compared to their diesel counterparts due to the additional weight of the battery and waste. In this study, 5 scenarios are defined to investigate electrification (20%, 40%, 60%, 80%, and 100%) of vehicles, based on the total distance travelled. For each scenario, 20% of the vehicles with the shortest travel distances are selected and added to the electrification pool, with corresponding scheduling of charging sessions after daily waste collection. While the area already includes some charging stations, it has been assumed an extension of the charging infrastructure to accommodate higher electrification levels in these scenarios. Changes in the charging process for the same vehicle arise due to variations in electrification levels and charging station availability, requiring optimization to ensure a minimum residual mileage (e.g., 20 km). Based on the total distance travelled, they are identified for electrification to ensure that they are feasible for electrification, based on the considered battery capacity. These electrified vehicles are then incorporated into the optimization model, while the remaining vehicles are considered fossil-fuel-powered. The baseline scenario represents a fleet with 100% fossil vehicles, used as a reference for comparison. Thus, 3 of 28 vehicles in the fleet are neglected from electrification since their assigned travel in the waste collection is higher than the battery capacity of considered EVs (Table 2). This selection criterion helps to minimize the impact on operational efficiency while maximizing the benefits of reduced fuel consumption and emissions. The electric vehicles are assumed to consume 0.8 kWh/km driven. Additional energy consumption for auxiliary loads, such as compaction and climate control, is estimated to add another 0.2 kWh/km. The total energy consumption for each vehicle is then used to estimate the overall electricity cost, using a rate of 0.15 €/kWh that allows for a detailed comparison between the fuel costs of diesel vehicles and the electricity costs of EVs. While capital and maintenance costs are important in waste collection operations, they are excluded to keep the scope centered on operational optimization. Moreover, a baseline scenario with 100% fossil vehicles is included to enable a comparative analysis of operational costs and emissions across electrification levels, with fixed capital costs excluded to isolate the operational aspects. In addition, this study compares Operational

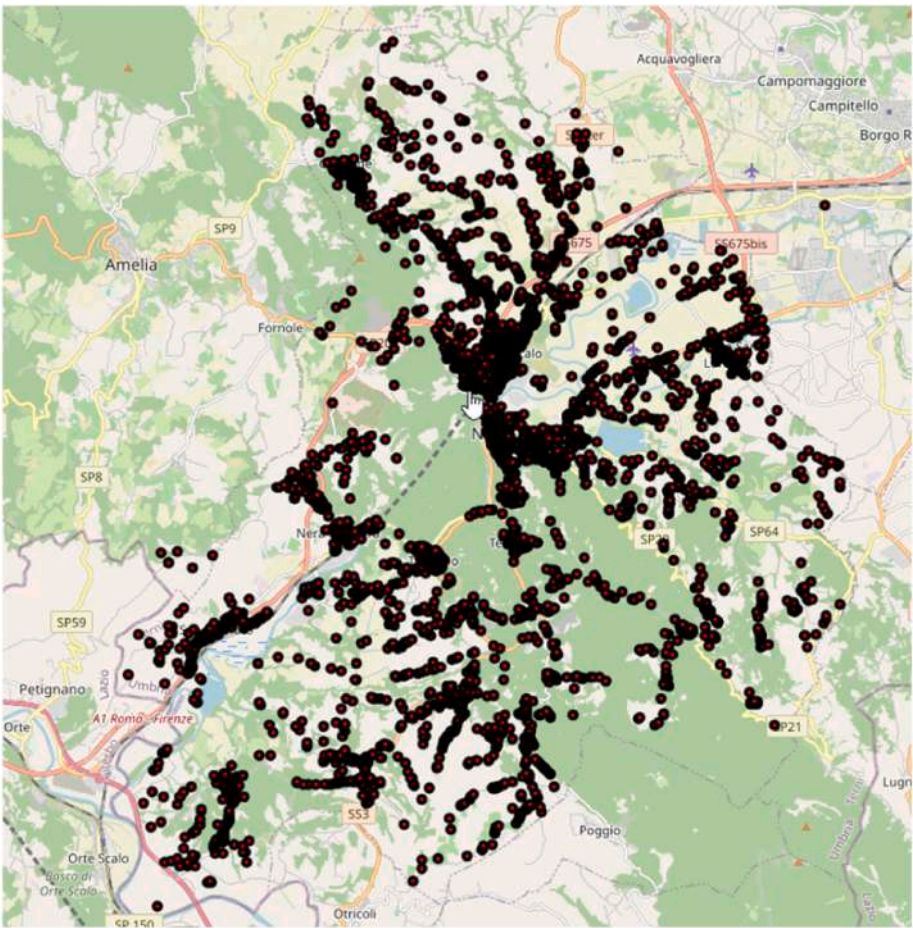


Fig. 3. – Distribution of bins in the district.

Table 2
– Fleet performance metrics.

Vehicle ID	Vehicle Size	Total Load	Total Duration (hr)	Number of Stops	Total Distance (km)	Estimated fuel cost (€)	Total emissions (kg CO ₂)
1	380	366	9.94	367	349.98	54.18	56.35
2	380	154	3.06	155	71.56	11.08	11.52
3	380	262	9.53	263	352.28	54.53	56.72
4	380	376	9.44	377	299.25	46.32	48.18
5	380	372	7.54	373	228.67	35.40	36.82
6	380	375	6.08	376	150.66	23.32	24.26
7	380	373	7.09	374	188.42	29.17	30.34
8	380	378	6.04	379	141.56	21.91	22.79
9	380	355	4.80	356	124.45	19.26	20.04
10	380	312	2.70	313	17.46	2.70	2.81
11	380	380	4.12	381	50.44	7.81	8.12
12	380	353	3.39	354	45.77	7.09	7.37
13	380	368	5.66	369	141.22	21.86	22.74
14	380	349	2.99	350	30.25	4.68	4.87
15	380	379	3.64	380	35.11	5.44	5.65
16	380	346	2.60	347	14.23	2.20	2.29
17	380	380	3.21	381	31.54	4.88	5.08
18	380	317	2.22	318	13.13	2.03	2.11
19	380	380	5.05	381	168.45	26.08	27.12
20	380	344	2.84	345	30.00	4.64	4.83
21	380	366	3.38	367	41.03	6.35	6.61
22	380	351	2.82	352	26.67	4.13	4.29
23	380	333	2.97	334	35.85	5.55	5.77
24	380	340	2.19	341	8.67	1.34	1.40
25	380	365	3.44	366	39.00	6.04	6.28
26	380	323	2.49	324	15.48	2.40	2.49
27	380	323	2.98	324	34.75	5.38	5.59
28	380	376	6.08	377	178.74	27.67	28.78
Total	10640	9696	128.29	9724	2864.58	443.44	461.20

Expenditures (OPEX), highlighting the benefits of adopting a hybrid fleet (EV + ICE). The overall economic convenience is not discussed. However, the outcomes of the study can be considered for assessing investment sustainability. The cost analysis includes:

- o Total fuel cost for diesel vehicles in the baseline scenario and electric vehicles in scenarios.
- o Total electricity cost for EVs in the electrification scenarios.
- o Combined fuel and electricity costs in the baseline scenario and electric vehicles in scenarios.

With respect to the emissions, diesel vehicles' emissions are calculated using a standard emission factor of 2.4 kg CO₂ per km, while electric vehicles' emissions are based on an emission factor of 0.5 kg CO₂ per kWh, accounting for the renewable energy fraction in the electricity mix. This differentiation helps in accurately assessing the potential reduction in greenhouse gas emissions through electrification (Fontaras et al., 2012). Finally, it was assumed that an increasing number of Charging stations is present and they can provide 22 kW as maximum peak power. Charging sessions can start at the end of daily activities and they can continue when the process stops. Operationally, vehicles operate daily for durations ranging from 2.19 to 9.94 h, with an average duration of approximately 4.58 h. They cover distances from 8.67 km to 352.28 km per day. Waste collection operations start at 6 a.m., and after completing their assigned routes, vehicles return to the parking area to be charged using the available infrastructure. Charging sessions begin at the end of daily activities and continue when operations halt, with charging stations providing up to 22 kW of peak power. The number of analyzed days (N_T) is fixed at 500 for all scenarios to identify periodicity across the various electrification levels.

5. Results analysis

5.1. CVRP analysis

In this Section, the results derived from the proposed optimized solution are presented, shedding light on the performance of the fleet of vehicles involved in waste collection and disposal. As the baseline scenario, all vehicles are diesel-powered and the results are derived using Google OR-Tools, an open-source suite specifically utilized for fleet optimization. Table 2 outlines the key metrics obtained from the analysis, providing valuable insights into the efficiency, productivity, and effectiveness of the fleet operations. Moreover, Fig. 4 shows the result of scheduling for each vehicle based on the new routes.

The key observations and insights into the optimized scheduling are mentioned below:

- **Load Optimization:** The analysis reveals that vehicles exhibit a high degree of load utilization, with most of them achieving near-maximum capacity utilization. Specifically, the average load utilization across all vehicles is 91.12%, indicating satisfaction with load optimization strategies and sustainable operations. The standard deviation of load utilization is 12.04%, highlighting the variability in load utilization among the vehicles. However, considering the goal of maximizing load utilization, the observed variability can be deemed acceptable as the majority of vehicles are utilizing their capacity efficiently.
- **Time Efficiency:** Vehicles with shorter total durations and fewer stops demonstrate enhanced operational efficiency, which translates to reduced driver fatigue, lower maintenance needs, and better fleet utilization. On average, vehicles spend 5.30 h on their routes, reflecting optimized scheduling that balances operational time and workload across the fleet. The variation in travel time among vehicles can be attributed to several factors including the geographical layout of the district traffic conditions and the distribution of waste collection points. In districts with diverse characteristics such as dense urban areas alongside sparsely populated regions, it is expected that vehicles will encounter varying levels of congestion and travel distances. Optimizing the routes based solely on equal travel time for all vehicles may not be the most efficient approach in such heterogeneous environments. Instead, the primary objective is to use vehicles in an optimized manner, ensuring that each vehicle covers its designated area effectively while minimizing overall operational costs and time. By allowing for flexibility in travel time and prioritizing route optimization based on factors such as distance, traffic patterns, and waste collection demand, the scheduling algorithm aims to maximize operational efficiency and resource utilization. Vehicles may spend more time in densely populated areas where waste generation is higher while minimizing travel time in less densely populated regions.
- **Route Optimization:** The average total distance travelled by each vehicle is 90.41 km with variations across vehicles. Efficient route planning minimizes travel distance while ensuring timely waste collection. This not only reduces fuel consumption and emissions but also improves service quality, particularly in areas with high population density or complex traffic patterns. The results highlight the importance of tailoring routes to account for urban congestion and waste generation variability. Therefore, optimizing routes based solely on distance travelled may overlook the nuanced spatial distribution of bin requests. By considering factors such as bin density and distribution, route optimization strategies can effectively balance travel distance with the fulfilment of collection requests, ensuring efficient resource utilization while meeting operational objectives.

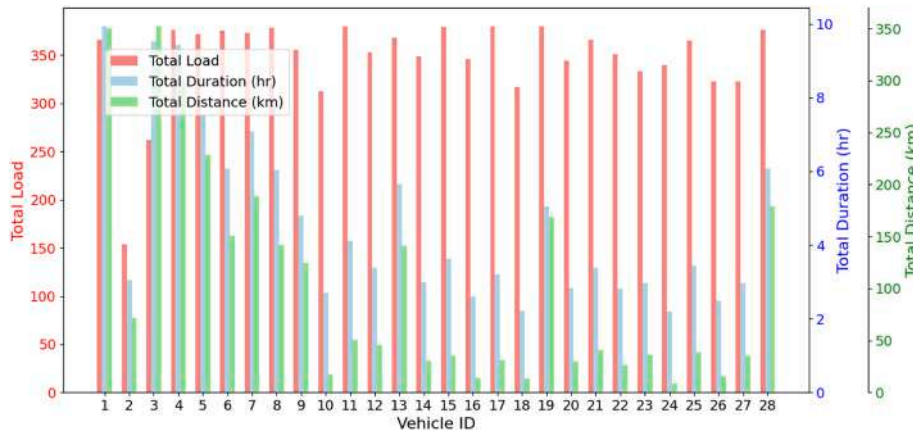


Fig. 4. – Key observation results based on the new route assignments.

In addition, the evaluation metrics are presented and used to assess the effectiveness of the fleet optimization strategies implemented for waste collection operations at ASM Terni S.p.A. The analysis is based on data obtained from the optimization algorithm and includes the following key metrics.

Fig. 5 depicts the distribution of vehicle utilization percentages. Showcasing the efficiency of resource allocation across different routes. Each bar in the histogram represents a range of utilization percentages, with the height indicating the frequency of routes falling within those utilization ranges. The utilization percentage is calculated by dividing the total load carried by each vehicle on its route by the total fleet load and multiplying by 100 to express it as a percentage. The distribution reveals insights into how effectively each vehicle's load capacity is utilized during the routes and routes with higher utilization percentages indicate more efficient resource usage, suggesting optimal load balancing and capacity utilization. By optimizing vehicle utilization, organizations can enhance operational efficiency, reduce costs, and improve overall fleet performance.

Fig. 6 shows the relationship between the total distance travelled and route duration. Routes with longer distances tend to exhibit higher durations, which reflects expected travel patterns. However, significant outliers may indicate operational inefficiencies caused by geographical factors or suboptimal load distribution. Such insights can help refine route assignments to balance distance and duration effectively. Each point on the plot represents a specific route, with the color indicating the corresponding vehicle ID, providing insights into the relationship between distance covered and time taken, and highlighting route efficiency and performance.

In addition, Fig. 7 highlights the average time spent at each stop. The clustering of stop times around certain values suggests consistent efficiency in waste collection across most routes. However, the longer durations observed in some cases could reflect delays caused by denser areas or more complex bin setups. Addressing these variabilities through targeted adjustments could further enhance fleet efficiency. The horizontal axis denotes the average duration per stop in seconds, while the vertical axis represents the frequency of occurrence. This visualization offers valuable insights into the variability and efficiency of service time at individual stops, aiding in the optimization of route planning and resource allocation.

5.2. Electrification results

This section provides results of electrification and scheduling charging sessions for different scenarios using MATLAB with YALMIP interface and Gorubi optimizer. The baseline scenario provides a reference point for comparing the impacts of electrification in the subsequent scenarios. The total fuel cost is €468.09, and the total emissions amount

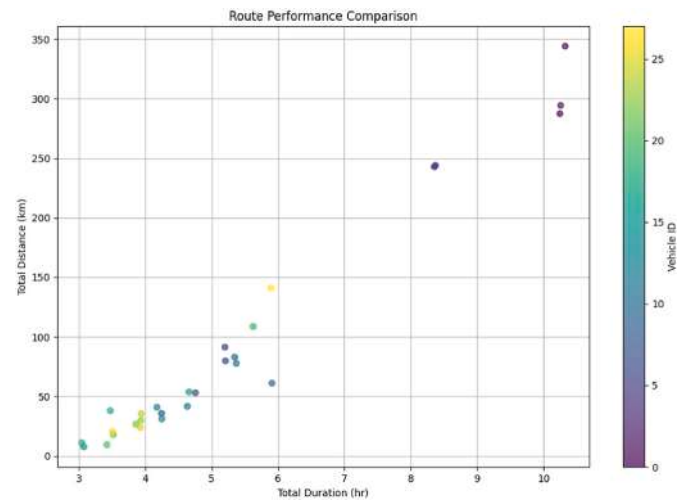


Fig. 6. – Route performance comparison scatter plot.

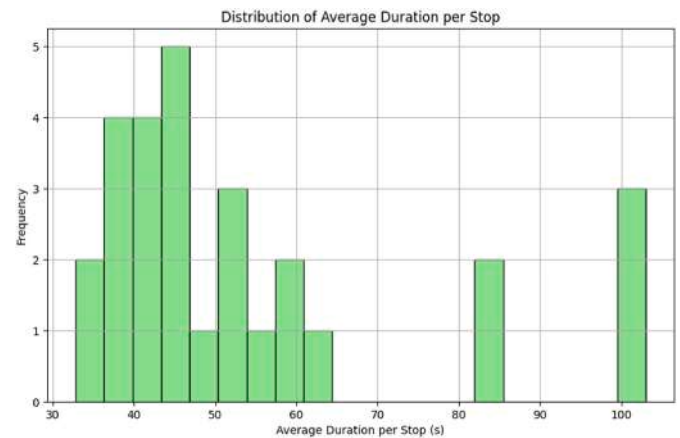


Fig. 7. – Distribution of average duration per stop.

to 6875.08 kg CO₂ for the daily waste collection operation of the fleet. There is no electricity consumption in this scenario since all vehicles are diesel-powered.

In Scenario 1, 20% of the vehicles with the lowest total distance travelled (among those traveling less than 300 km) are electrified. This results in the electrification of 5 vehicles out of the 28 in the fleet. The optimization model for charging sessions allows to assess that:

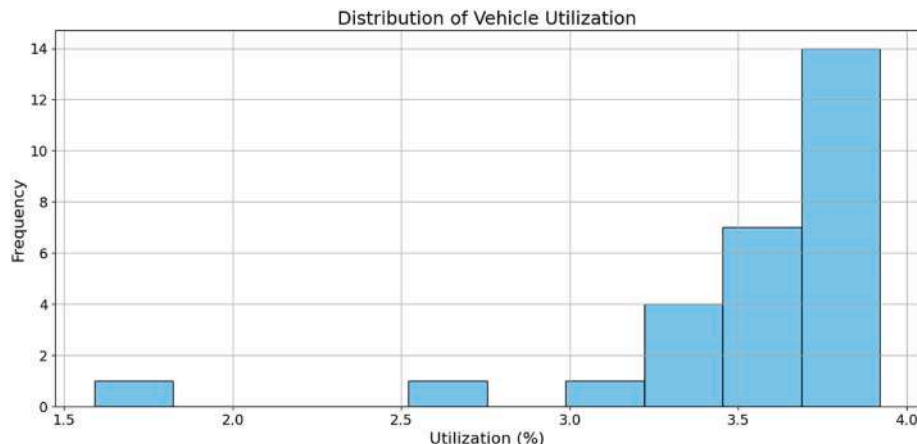


Fig. 5. – Distribution of vehicle utilization.

- If N_{CS} is equal to 2, an infeasible problem is identified that it has been calculated that the minimum charging infrastructure requires N_{CS} equal to 3,
- When N_{CS} is equal to 3, the SoC of the 5 vehicles varies according to Fig. 8; notably, the EV that travels the greatest distance is always charged whilst the others are charged every 3 days on average,
- minimum SoC among all the trends of EVs is equal to 6.8 %,
- considering the trends of EVs for each EV, standard deviations were calculated. Among the calculated variances, the greatest value is 38.3 %.

In Scenario 2, 40% of the vehicles with the lowest total distance travelled (among those traveling less than 300 km) are electrified. This results in the electrification of 10 vehicles out of the 28 in the fleet. The optimization model for charging sessions allows to assess that:

- if N_{CS} is equal to 4, an infeasible problem is identified so that it has been calculated that the minimum charging infrastructure requires N_{CS} equal to 5,
- when N_{CS} is equal to 5, the SoC of the 5 vehicles that have been already reported in Fig. 8 varies according to Fig. 9,
- minimum SoC among all the trends of EVs is equal to 6.8 %,
- considering the trends of EVs for each EV, standard deviations were calculated. Among the calculated variances, the greatest value is 38.3 %.

In Scenario 3, 60% of the vehicles with the lowest total distance travelled (among those traveling less than 300 km) are electrified, corresponding to the electrification of 15 vehicles out of the 28 in the fleet. The optimization model for charging sessions allows to assess that:

- if N_{CS} is equal to 5, an infeasible problem is identified that it has been calculated that the minimum charging infrastructure requires N_{CS} equal to 6,
- when N_{CS} is equal to 6, the SoC of the 5 vehicles that have been already reported in Fig. 9 varying according to Fig. 10, it can be noted that the vehicles have greater variance,
- minimum SoC among all the trends of EVs is equal to 6.8 %,
- considering the trends of EVs for each EV, standard deviations were calculated. Among the calculated variances, the greatest value is 38.3 %.

In Scenario 4, 80% of the vehicles with the lowest total distance travelled (among those traveling less than 300 km) are electrified. This results in the electrification of 20 vehicles out of the 28 in the fleet. The

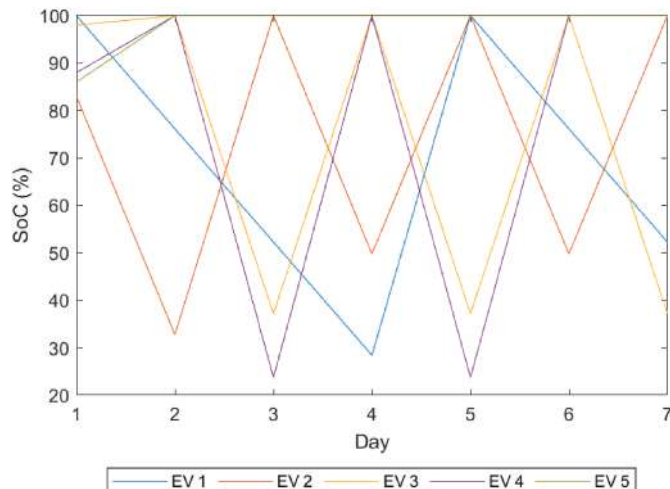


Fig. 8. – EV charging sessions under Scenario 1 assuming N_{CS} equal to 3.

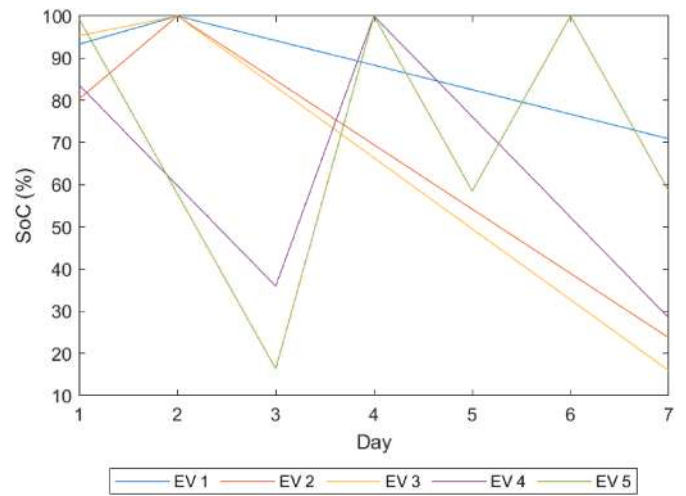


Fig. 9. – EV charging sessions under Scenario 2 assuming N_{CS} equal to 5.

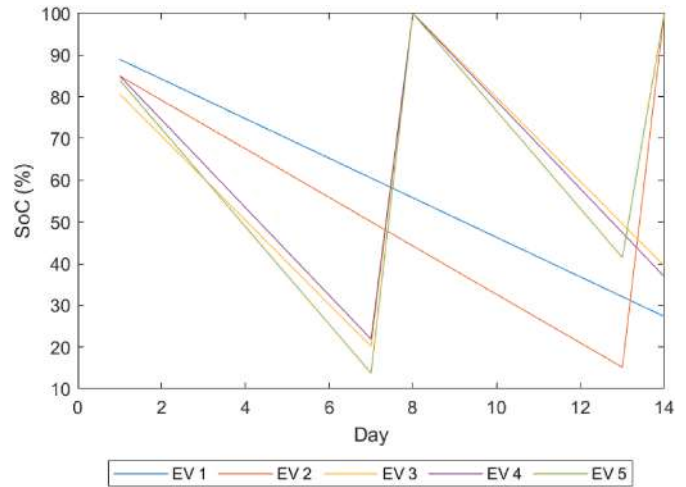


Fig. 10. – EV charging sessions under Scenario 3 assuming N_{CS} equal to 6.

optimization model shows that 6 CS are still enough to supply 20 EVs, the corresponding charging sessions are reported in Fig. 11. The minimum SoC of the EVs is 6.8 %, whilst the greatest standard deviation for a single EV was calculated as equal to 38.3 %. This scenario shows that an

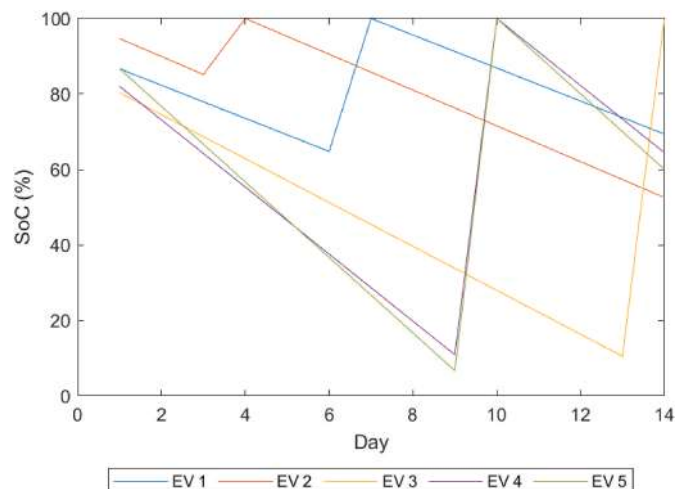


Fig. 11. – EV charging sessions under Scenario 4 assuming N_{CS} equal to 6.

optimized management of the charging sessions could dramatically reduce the number of charging stations especially if the fleet has more than 10 vehicles.

By analyzing various levels of fleet electrification, the economic and environmental outcomes can be evaluated, focusing on cost savings and emissions reduction in Fig. 12.

As the fleet electrifies, fuel costs decrease significantly across all scenarios. This reduction is due to the lower operating costs of EVs compared to diesel vehicles. For instance, in Scenario 5, which represents the highest level of electrification, the fuel cost drops dramatically to €114.75 from the baseline of €468.09, marking a reduction of approximately 75.5%. Conversely, electricity costs rise with higher electrification levels, which is expected as more EVs require more electricity for charging. In Scenario 5, the total electricity cost reaches €324.35. Despite this increase, the combined cost of fuel and electricity shows a downward trend, indicating a reduction in total operational costs. Scenario 5 demonstrates the most significant reduction in total costs, with a combined cost of €439.10 compared to the baseline of €468.09.

The total operational costs, encompassing both fuel and electricity, decrease as the percentage of electrified vehicles increases. This trend highlights the cost-effectiveness and feasibility of electrifying the fleet. For instance, Scenario 5 achieves a total cost reduction of 6.19%, illustrating substantial savings when the entire fleet is electrified.

A major advantage of fleet electrification is the significant reduction in greenhouse gas emissions. Each scenario shows a progressive decrease in emissions as more vehicles are electrified. For example, Scenario 1 achieves a modest reduction of 1.91%, whereas Scenario 5 achieves a substantial reduction of 59.76%. The total emissions in Scenario 5 are 2766.60 kg CO₂, down from the baseline of 6875.08 kg CO₂. This reduction is primarily due to the lower emission factors associated with electricity compared to diesel fuel.

6. Conclusion

This study integrates fleet optimization and electrification strategies to enhance waste collection operations at ASM Terni S.p.A., focusing on economic and environmental benefits. The optimized routing and scheduling resulted in significant improvements in load utilization, time efficiency, and overall operational performance. The fleet optimization strategies effectively utilized the vehicles' capacities, achieving an average load utilization of 91.12% with a standard deviation of 12.04%,

indicating efficient resource allocation. These results demonstrate the success of the optimization techniques in minimizing operational time and distance while maximizing resource utilization.

In addition, electrification scenarios were analyzed to evaluate their economic and environmental impacts. The economic analysis revealed substantial cost savings as the fleet electrification level increased. With 100% of electrification, the fuel cost dropped by 6.19%, marking an emission reduction of approximately 60%, highlighting the potential environmental benefits of transitioning to electric vehicles in waste collection. The strategic planning of charging schedules ensured operational efficiency, minimizing downtime and ensuring vehicles were ready for their next duty cycles. In Scenario 5, vehicles utilized different charging stations efficiently, with detailed scheduling that considered the initial state of charge, required energy, and station capacity. This careful planning is crucial for maintaining fleet efficiency during the transition to electrification.

Overall, this study provides a comprehensive framework for integrating fleet optimization and electrification in urban waste management systems. The demonstrated economic and environmental benefits suggest that broader application of these strategies can lead to more sustainable and cost-effective waste collection operations. The significant reductions in operational costs and emissions underline the potential for substantial improvements through the adoption of electric vehicles and optimized routing strategies, providing a model for other urban waste management systems to follow.

The authors plan to extend the study to the Terni district which includes a higher number of customers, vehicles, and available charging stations, which definitely creates a bigger challenge in optimizing routes, towards electrification, and scheduling charging sessions. In addition, exploring the use of vehicle-to-grid (V2G) technology, which allows electric vehicles to return energy to the grid when not in use is another goal in the future. This can help balance the grid, especially during peak demand times, and provide an additional revenue stream. Moreover, the authors will investigate the optimal balance between grid energy and renewable energy sources for charging the fleet. Develop strategies to maximize the use of renewable energy, such as solar or wind power, to reduce dependency on the grid and lower overall carbon footprints.

Moreover, implementing real-time dynamic routing algorithms can adapt to changing conditions such as traffic patterns, weather conditions, and waste generation rates in order to ensure that the fleet operates at maximum efficiency under varying circumstances. By focusing on

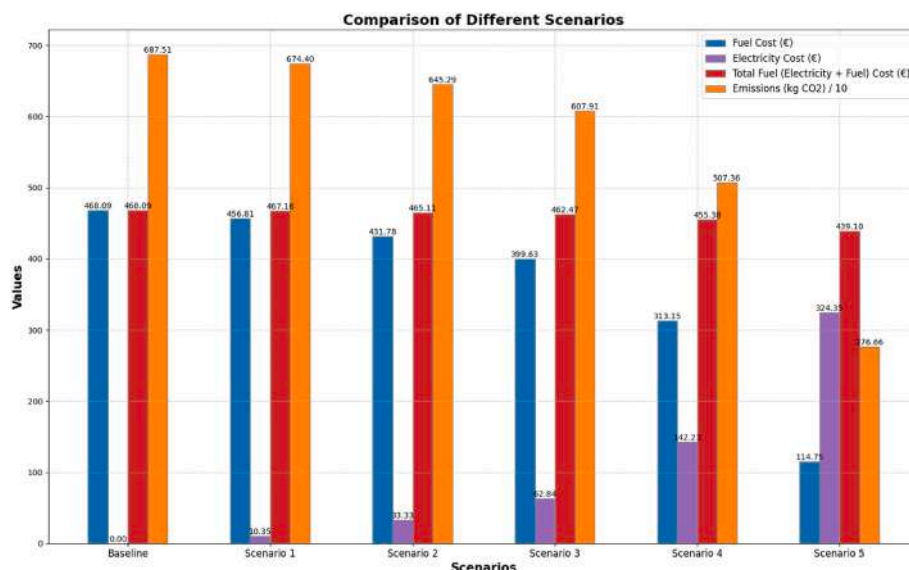


Fig. 12. – Comparing electrification scenarios with diesel/baseline scenarios of the waste collection fleet.

these areas, future plans can build on the successes of the current study, leading to more efficient, cost-effective, and environmentally friendly waste collection operations.

CRediT authorship contribution statement

M. Ghoreishi: Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **F. Santori:** Writing – review & editing, Supervision, Methodology. **L. Carloni:** Resources, Data curation. **M. Cresta:** Resources, Investigation. **A. Geri:** Supervision, Conceptualization. **T. Bragatto:** Writing – review & editing, Validation, Software, 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.

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Data availability

The data that has been used is confidential.

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