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EVALUATING THE EFFICIENCY OF OPTIMIZED WASTE COLLECTION ROUTES USING DATA ENVELOPMENT ANALYSIS

ABSTRACT: Efficient waste collection has an important role in sustainable urban transport systems, since it directly affects operational costs, fuel consumption, and environmental performance. This paper explores how VRP-based route planning combined with data envelopment analysis can help evaluate and improve waste collection routes in the city of Kragujevac. Alternative route configurations were generated using the Vehicle Routing Problem (VRP) solver implemented in ArcGIS Network Analyst, with the aim of reducing travel distance while maintaining the required level of collection service. To assess their performance, an input-oriented DEA model assuming variable returns to scale was applied to evaluate the pure technical efficiency of the optimized routes. Operational factors, specifically route length and travel time, were selected as input variables to be minimized, while indicators related to waste collection services were used as outputs.
By using this approach, it is possible to distinguish the efficient routes from the inefficient ones and identify specific ways to reduce resource consumption without compromising service quality. This paper provides a decision-support framework for fleet management in public utilities by combining VRP-based route planning with multidimensional efficiency evaluation.

KEYWORDS: municipal waste management, data envelopment analysis (DEA), geographic information systems (GIS), route optimization, waste collection

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PROCENA EFIKASNOSTI OPTIMIZOVANIH RUTA ZA SAKUPLJANJE OTPADA KORIŠĆENJEM ANALIZE OBAVIJANJA PODATAKA

REZIME: Efikasno sakupljanje otpada ima važnu ulogu u održivim sistemima urbanog transporta, budući da direktno utiče na operativne troškove, potrošnju goriva i ekološke performanse. Ovaj rad istražuje kako kombinovanje planiranja ruta zasnovanog na problemu rutiranja vozila (VRP) sa analizom obavijanja podataka (DEA) može doprineti proceni i unapređenju ruta za sakupljanje otpada u gradu Kragujevcu. Alternativne konfiguracije ruta generisane su korišćenjem VRP solvera implementiranog u ArcGIS Network Analyst, sa ciljem smanjenja dužine putovanja uz zadržavanje zahtevanog nivoa usluge sakupljanja otpada. Za procenu njihovih performansi primenjen je DEA model orijentisan na ulaze, uz pretpostavku varijabilnih prinosa na obim, kako bi se ocenila čista efikasnost optimizovanih ruta. Kao ulazne varijable koje je potrebno minimizovati odabrani su operativni faktori, odnosno dužina rute i vreme putovanja, dok su kao izlazi korišćeni pokazatelji povezani sa uslugom sakupljanja otpada.

Primenom ovog pristupa moguće je razlikovati efikasne od neefikasnih ruta i identifikovati konkretne mogućnosti za smanjenje potrošnje resursa bez ugrožavanja kvaliteta pružene usluge. Ovaj rad predstavlja okvir za podršku odlučivanju u upravljanju voznim parkom javnih komunalnih preduzeća, zasnovan na kombinovanju planiranja ruta primenom VRP-a i višedimenzionalne procene efikasnosti.

KLJUČNE REČI: upravljanje komunalnim otpadom, analiza obavijanja podataka (DEA), geografski informacioni sistemi (GIS), optimizacija ruta, sakupljanje otpada.

INTRODUCTION

Municipal solid waste (MSW) is an unavoidable consequence of most human activities and has become an increasingly important environmental concern (Choiron et al. 2023). It is also recognized as a significant contributor to climate change and global warming, highlighting the need for more sustainable approaches to waste management (Son, 2014; Amal et al., 2020). Effective MSW management is therefore an essential public service, while appropriate regulations can encourage greater innovation, sustainability, and operational efficiency within the sector. Over recent decades, considerable attention has been given to improving MSW management systems worldwide, particularly by enhancing the efficiency of their individual components. In general, an MSW management system consists of five main stages: waste generation, collection and transportation, transfer, treatment, and final disposal (Bošković et al. 2024). Among these stages, waste collection constitutes a substantial share of municipal expenditure (Daraio et al. 2024). Namely, the waste collection and transportation represent a major logistical activity in urban areas and typically account for approximately 60-80% of the total costs associated with waste management. Improving this part of the system is therefore particularly important for increasing energy efficiency and reducing the financial burden on municipalities. Furthermore, efficient MSW collection plays a central role in supporting the transition toward a circular economy and the development of more sustainable modern communities (Sousa et al. 2024). This phase of MSW management system represents a significant cost to municipal budgets due to fuel consumption, labour requirements, vehicle maintenance, and travel time. Consequently, improving the efficiency of waste collection routes has become an important goal for municipalities seeking to reduce operating costs while improving environmental sustainability.

In recent years, geographic information systems (GIS) have become one of the most widely used decision-support tools for planning and optimizing waste collection routes. GIS is a powerful tool that enables precise mapping, spatial analysis, and route optimisation, ultimately leading to cost savings and improved service quality (Robin et al. 2019; Das et al. 2024). GIS enables the implementation of spatial analysis, using well-established routing algorithms like the Dijkstra algorithm to determine the shortest or most cost-effective routes between various points (Dijkstra, 1959; Amal et al. 2020). Route optimization contributes to reducing travel distance, travel time, fuel consumption, and greenhouse gas emissions, thereby supporting the development of sustainable urban transport systems.

Although the optimization process can improve route planning, it does not provide a comprehensive assessment of operational efficiency. Route optimization is generally based on minimizing a predefined objective function, whereas the overall performance of a route depends simultaneously on multiple operational and environmental indicators. Therefore, additional evaluation methods are required to determine whether optimized routes actually utilize available resources efficiently. In this context, an efficiency assessment approach capable of considering several variables or performance indicators simultaneously can provide a more comprehensive evaluation of the resulting routes. Data Envelopment Analysis (DEA) is one of the most widely used methods for evaluating the efficiency of systems that involve multiple inputs and outputs. DEA is a non-parametric mathematical programming technique widely applied

for measuring the relative efficiency of comparable decision-making units (DMUs) (Li & Xu, 2008). Unlike conventional performance indicators, DEA simultaneously evaluates several input and output variables without requiring assumptions regarding their functional relationship. In transportation and logistics systems, DEA has been successfully applied for evaluating vehicle fleets, public transport systems, ports, airports, and municipal services. However, studies integrating VRP-based route planning with DEA for municipal solid waste collection remain relatively limited.

The city of Kragujevac in the Republic of Serbia provides an appropriate case study for investigating the integration of spatial optimization and efficiency evaluation. Waste collection routes in Kragujevac have already been optimized using the ArcGIS Network Analyst extension, resulting in reductions in travel distance for several routes (Bošković & Jovičić, 2015; Bošković et al. 2024). However, the efficiency of these optimized routes has not yet been assessed by considering multiple operational performance indicators simultaneously.

Therefore, this study aims to combine VRP-based route planning in ArcGIS Network Analyst with DEA to evaluate municipal waste collection routes. The analysis compares the existing routes with the optimized ones using an input-oriented DEA model with variable returns to scale. In this way, the routes are evaluated not only according to the improvements achieved through optimization, but also according to how efficiently the available resources are used. Combining VRP-based route planning and DEA makes it possible to examine route performance from both spatial and operational perspectives. The findings can help municipalities better understand the effects of route optimization, improve the use of their vehicle fleets and other resources, and make waste collection operations more efficient as well as sustainable.

METHODOLOGY OF RESEARCH

With increasing MSW generation and growing operational demands, efficient waste collection and transportation are becoming increasingly important for sustainable waste management. Since waste collection accounts for a substantial share of overall waste management costs, careful route planning and efficient use of available resources are essential for improving system performance (Bošković et al. 2024). The methodological framework used in this study is presented in Figure 1. The analysis begins with the collection and preparation of operational and spatial data describing the existing waste collection system. These data are then used to reconstruct the current collection routes and develop the street network required for the subsequent VRP-based route planning in ArcGIS Network Analyst. In the next step, alternative route configurations are generated using the VRP solver in ArcGIS Network Analyst based on the developed street network and defined operational constraints, followed by a comparison with the existing routes. The final stage uses an input-oriented DEA model under the variable returns to scale assumption to assess the relative efficiency of the analysed routes.

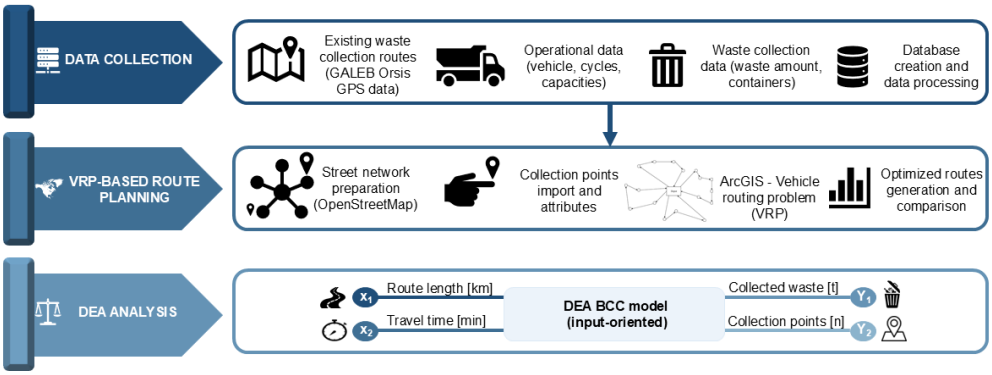


Figure 1 Methodological framework of research

This methodological framework enables not only a comparison between the existing and alternative route configurations but also an examination of whether shorter and better-planned routes lead to more efficient use of available resources.

Study area and data collection

The study was conducted using MSW collection routes operated by the Public Utility Company (PUC) Šumadija in the city of Kragujevac, Serbia. The company is responsible for the collection and transportation of mixed municipal solid waste and recyclable waste generated in residential, commercial, and public areas of the city. Waste collection is organized according to the characteristics of different parts of the city. Collection frequency varies between streets and neighbourhoods depending on the amount and type of waste generated, housing characteristics, the number of commercial facilities and waste containers, as well as local traffic conditions. Based on these characteristics, the city is divided into six waste collection zones: Extra, First, Second, Third, Fourth, and Fifth Zone (PUC Šumadija, 2026).

Different types of vehicles are used depending on the waste collection system and the type of container being serviced. The municipal fleet includes 18 waste collection vehicles that collect waste from 1.1 m³ containers and 140 litres household bins, while larger containers are serviced by hook-lift vehicles. Additional vehicles are used for specific operations, including the collection of bulky waste. The collection system covers approximately 2,300 containers located throughout the city, together with around 4,000 140 litres bins distributed to households in residential areas. A separate system is in place for recyclable packaging waste. It includes 120 plastic containers of 1.1 m³ placed at 60 locations across the city. In rural areas, households use waste collection bags, which are distributed twice a month (PUC Šumadija, 2026).

Although the municipal collection system covers different waste streams, container types, and collection arrangements, this study focuses on Monday routes for mixed municipal solid waste. A total of 14 Monday routes were included in the DEA efficiency assessment. Of these, nine routes primarily serving 1.1 m³ containers were selected for VRP-based route planning, while routes MON14 - MON18, which predominantly serve individual household bins, were retained only in the DEA analysis.

Spatial data preparation and GIS database development

Route optimization requires a spatial database that accurately represents both the street network and the existing waste collection system. The data used in this study were obtained from the operational records of PUC Šumadija Kragujevac and complemented by spatial data prepared in a GIS environment. The database included three main spatial components: the street network, georeferenced waste collection points, and the existing routes used by waste collection vehicles (Bošković et al. 2024). Data describing the existing routes, including vehicle movements and route-related operational parameters, were obtained from the GALEB Orsis11 (Galeb System, 2023) fleet monitoring software used by the company.

Street network preparation

The quality of route optimization depends strongly on how accurately the street network reflects the actual conditions in which waste collection vehicles operate. In this study, the street network for the City of Kragujevac was developed using OpenStreetMap data (OpenStreetMap, 2023). The street segments extending beyond the administrative boundary of the city were retained when they formed part of the existing waste collection routes. The network was represented by polyline features, with each street segment linked to relevant attributes such as street name and length. To reflect actual vehicle movement more realistically, one-way streets and turning restrictions were also incorporated into the network. These constraints ensured that the routes generated during the optimization process followed the traffic rules represented in the developed street network.

Waste collection points

Waste collection points were mapped using the available spatial data and existing digital maps, allowing their locations to be accurately represented within the study area. Each point was linked to a set of operational attributes, including the type and number of waste containers, collection day, service time, street location, and other relevant field information. The analysis was limited to collection points equipped with 1.1 m³ containers for mixed municipal solid waste and included in the Monday collection schedule. The selected points were linked to the prepared street network and defined as required stops in the subsequent route optimization. Their spatial distribution across the study area is shown in Figure 2.

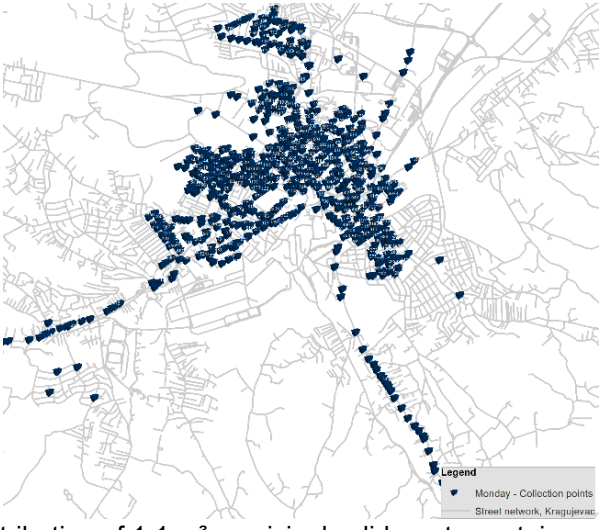


Figure 2 Spatial distribution of 1.1 m³ municipal solid waste containers served on Mondays

This spatial representation provides a clear picture of the collection system and establishes the basis for the route analysis presented in the following section.

Existing route characteristics and VRP-based route planning in ArcGIS

Before optimization, the operational characteristics of the 14 selected Monday routes were compiled to establish the baseline scenario. The dataset covered the main characteristics of each route, including the service area, number of collection points, number of 1.1 m³ containers and waste bins, amount of collected waste, route length, travel time, number of collection cycles, and estimated fuel consumption (Table 1). These data were used to describe the baseline operating conditions and later served as a reference for evaluating the changes achieved through route optimization. Since fuel consumption was not measured directly for individual routes, it was estimated using a representative waste collection vehicle with an average fuel consumption of 55.6 liters/100 km. The same consumption rate was applied to the distance travelled on each route to obtain the corresponding estimated fuel consumption.

Table 1 Operational characteristics of existing waste collection routes

*	Route	Service area	Collection points [n]	1.1 m³ containers [n]	Waste bins [n]	Collected waste [t]	Route length [km]	Travel time [min]	Collection cycles [n]	Estimated fuel consumption per route [l]
1.	MON11	Centrala radionica i Pivara	71	160	0	7.64	39.89	177.97	2	22.18
2.	MON12	Erdoglija	75	206	0	10.54	36.20	114.00	2	20.13
3.	MON13	BKM + Kneza Mihaila + Kraljevačkog bataljona	81	187	0	9.44	31.53	102.47	1	17.53
4.	MON14	Korićani	32	0	666	3.22	28.88	153.75	1	16.06
5.	MON15	Stanovo	33	0	771	7.52	28.16	146.27	1	15.66
6.	MON16	Ibarski rudara + Drenovac + Đuriselo	17	29	519	4.12	54.53	163.82	1	30.32
7.	MON17	Ćava	21	4	627	9.16	49.25	171.08	2	27.38
8.	MON18	Grošnica + Ćava	25	2	649	6.20	46.64	144.17	1	25.93
9.	MON21	Centar + Beloševac	88	207	0	10.52	39.62	121.83	2	22.03
10.	MON22	Aerodrom	63	205	0	12.40	29.88	105.20	2	16.61
11.	MON23	Mala Vaga + Erdoglija	79	201	0	8.74	37.74	164.38	2	20.98
12.	MON31	Centar	67	202	0	7.74	29.55	105.87	2	16.43
13.	MON32	Centar 2	86	220	0	9.80	37.03	136.38	2	20.59
14.	MON33	Bubanj + Vašarište	82	224	0	8.77	35.91	131.60	2	19.97

Route planning was carried out in ArcGIS Network Analyst 10.8 using its Vehicle Routing Problem (VRP) solver (ESRI, 2026). VRP is commonly used to organize vehicle routes when a set of locations has to be served under operational constraints, which makes it suitable for municipal waste collection (Xin et al., 2021). In this study, each predefined Monday route was considered separately rather than solving a single fleet-allocation problem for the entire city. Collection points remained assigned to their existing routes, while their visiting order and distribution between collection cycles could be changed. Although the VRP can be solved using either distance or travel time as the impedance (Bošković et al. 2024; ESRI, 2026), distance was used as the routing criterion in this study.

Each collection point was represented as a required node, with demand based on the number of 1.1 m³ containers at that location. The same vehicle capacity was used for all analysed routes. Vehicles departed from the municipal garage of PUC Šumadija and returned there after completing the route, while the Jovanovac landfill was used as the unloading location. Depending on the number of containers to be serviced, collection was completed in one or two collection cycles. Most routes were completed in two collection cycles, with unloading at the landfill after each cycle. The total route length covered the complete vehicle movement, including travel from the municipal garage, visits to all assigned collection points, unloading at the landfill, and the final return to the garage. Service times for individual collection points were obtained from the operational database and were kept unchanged during route planning.

The street network was prepared to reflect actual vehicle movement as closely as possible. In addition to correct network connectivity and elevation levels at grade-separated crossings, one-way streets and turning restrictions were included. Shortest paths between network locations were calculated over this network, while the order in which collection points were visited was determined by the heuristic procedure used by the Network Analyst VRP solver. Consequently, the resulting route configurations are considered feasible improvements over the recorded routes, without implying that they represent mathematically proven global optima. Since the collection service was represented by point locations and not by street segments, the problem was formulated as a node-routing VRP rather than an arc-routing problem.

Data envelopment analysis

The final stage of the methodological framework focused on determining whether the improvements achieved through VRP-based route planning were also reflected in the operational efficiency of the collection system. For this purpose, DEA was applied to evaluate and compare the efficiency of the existing and optimized waste collection routes. The DEA is a linear programming approach widely used to assess the relative efficiency of comparable decision-making units (DMUs). It evaluates how efficiently each unit transforms multiple inputs into outputs by comparing its performance with an empirical efficiency frontier formed by the best-performing units. Depending on the assumptions of the model, DEA can account for different returns to scale, allowing efficiency to be assessed under different operating conditions (García-Sánchez, 2008). DEA efficiency can be assessed under either constant returns to scale (CRS) or variable returns to scale (VRS), depending on the assumptions regarding the relationship between inputs and outputs. Charnes et al. (1978) introduced a linear programming approach for evaluating the relative efficiency of decision-making units under the assumption of CRS. The CRS model assumes that all DMUs operate at an optimal scale and that changes in inputs result in proportional changes in outputs. For *n* entities using *m* inputs *x* to generate *s* outputs *y*, the input-oriented model seeks to minimize the required level of inputs while maintaining the observed output levels. The model can be expressed as (Mirmozaffari & Kamal, 2024):

$$\theta^* = min\theta \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j \, x_{ij} \; \leq \theta x_{i0}, i = 1,2, \dots, m \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j \, y_{rj} \; \geq y_{r0}, r = 1,2, \dots, s \tag{3}$$

$$\lambda_j \geq 0, j = 1,2, \dots, n \tag{4}$$

where λ represents non-negative intensity variables used to construct the reference frontier, while θ represents the technical efficiency score of the evaluated entity. A value of θ closer to 1 indicates a higher level of relative efficiency. Banker et al. (1984) subsequently extended the CRS model by introducing the VRS framework. The VRS model incorporates an additional convexity constraint: $\sum_{j=1}^{n} \lambda_j = 1$, which allows efficiency to be assessed independently of differences in operating scale. While the CRS model provides an overall technical efficiency (TE) score that incorporates both technical and scale effects, the VRS model measures pure technical efficiency (PTE) by accounting for variations in scale. Consequently, comparing the efficiency scores obtained under the two models makes it possible to identify whether inefficiency arises from managerial or operational performance or from operating at a non-optimal scale.

Since the objective of this study was to determine the potential reduction of operational resources while maintaining the current service level, an input-oriented BCC model assuming VRS was adopted. Each waste collection route operated on Mondays was considered a DMU. The number of DMUs should be carefully considered when applying DEA, particularly in relation to the number of input and output variables included in the model. Using too many variables with a limited number of DMUs can make it difficult for the model to distinguish between efficient and inefficient units. As a general rule of thumb, the number of DMUs should therefore be at least twice the combined number of inputs and outputs (Golany & Roll, 1989). The selection of input and output variables was based on operational characteristics commonly used in municipal waste collection studies. As shown in Figure 1, two inputs and two outputs were included in the DEA model. Route length, expressed in kilometres, and travel time, expressed in minutes, were selected as input variables, while the amount of collected waste, expressed in tonnes, and the number of collection points served along each route were used as outputs. The selected inputs represent the main operational resources associated with route performance and are therefore intended to be minimized, whereas the outputs reflect the level of waste collection service that should be maintained. The amount of collected waste is frequently used as an output variable in DEA-based assessments of waste collection systems, as it directly reflects the service provided by each route (Lombardi et al., 2021). Fuel consumption could also be considered a relevant operational and environmental indicator. However, in this study, fuel consumption was estimated as a direct function of the distance travelled rather than measured independently for each route. Including both route length and estimated fuel consumption as separate DEA inputs would therefore introduce redundant information into the model. For this reason, fuel consumption was excluded from the DEA specification.

To distinguish between efficiency within each scenario and changes resulting from route optimization, the DEA was carried out in two stages. In the first stage, a scenario-specific analysis was performed, in which the existing and optimized route scenarios were evaluated separately using the same input-oriented BCC/VRS model. This analysis provided an overview of the relative efficiency structure within each scenario. However, since each scenario generates its own efficiency frontier, the resulting efficiency scores cannot be directly compared to determine whether optimization improved the efficiency of individual routes. For this reason, a second-stage common-frontier analysis

was performed (Ruiz & Sirvant, 2016; Nasrabadi, 2018). The 14 existing routes and their 14 corresponding optimized configurations were combined into a single dataset of 28 observations and evaluated simultaneously against the same BCC/VRS efficiency frontier. The input-output specification was kept unchanged: route length and travel time were used as inputs, while collected waste and the number of collection points served were treated as outputs. The main difference compared to the first stage of analysis was that both the existing and optimized configurations were evaluated against the same reference set. Under the common-frontier approach, the efficiency change for route i was calculated as:

$$\Delta\theta_i = \theta_{i,O} - \theta_{i,\ E} \tag{5}$$

where $\theta_{i,\ E}$ represents the efficiency score of the existing route configuration and $\theta_{i,O}$ represents the score of its optimized configuration, with both scores obtained from the common-frontier model. A positive value of $\Delta\theta_i$ indicates an improvement in relative efficiency following optimization, zero indicates no change, and a negative value indicates a decrease. Since both configurations are evaluated against the same frontier, a route that remains unchanged in terms of its inputs and outputs will necessarily receive the same efficiency score in both configurations.

All DEA models were solved using the Simplex linear programming algorithm implemented in Microsoft Excel Solver.

RESULTS AND DISCUSSION

Route optimization is an important part of the operational planning of PUC Šumadija Kragujevac, as the organization of collection routes directly affects the distance travelled by waste collection vehicles and the resources required to provide the service. Detailed characteristics of the existing and optimized routes are provided in Table 2, based on operational data obtained from the GALEB Orsis11 fleet monitoring software. The existing routes were compared with alternative configurations generated using the VRP solver in ArcGIS Network Analyst, with the aim of identifying shorter travel paths without changing the required level of waste collection service. The analysis showed that the potential for improvement was not the same across all routes. Routes MON14-MON18, where waste is predominantly collected from individual household bins, were excluded from further optimization. Their collection pattern is closely linked to the spatial distribution of individual households and the layout of the local street network, leaving relatively little flexibility to reorganize the sequence of collection. The optimization therefore focused on routes serving 1.1 m³ containers for mixed municipal solid waste, where changes in the order and configuration of collection points offered greater opportunities to reduce the distance travelled.

Table 2 Summary of VRP-based route planning results

Route	Collection cycles [n]	Existing route [km]	Optimized route [km]	Distance saving [km]	Distance saving [%]	Collection points [n]	1.1 m³ containers [n]	Max. containers per cycle I [n]	Max. containers per cycle II [n]	Max collection points - cycle I [n]	Max collection points - cycle II [n]
MON11	2.00	39.89	39.89	0.00	0.00%	71	160	90	70	40	31
MON12	2.00	36.20	32.59	3.61	9.97%	75	206	110	96	40	35
MON13	1.00	31.53	31.53	0.00	0.00%	81	187	187	/	81	/
MON21	2.00	39.26	39.26	0.00	0.00%	88	207	107	100	45	43
MON22	2.00	29.88	29.08	0.80	2.69%	63	205	105	100	35	28
MON23	2.00	37.74	36.97	0.77	2.05%	79	201	105	96	43	36
MON31	2.00	29.55	28.20	1.35	4.55%	67	202	105	97	35	32
MON32	2.00	37.03	29.70	7.33	19.81%	86	220	115	105	46	40
MON33	2.00	35.91	33.30	2.61	7.28%	82	224	125	99	46	36

Among the routes included in the optimization, MON11, MON13, and MON21 remained unchanged. Under the defined network conditions and optimization criteria, no shorter alternative was identified, and the optimized solution therefore followed the same route as the existing one. This indicates that these routes were already well organized from the perspective of travel distance and that further spatial rearrangement alone would provide little or no additional benefit.

The situation was different for the remaining routes, where VRP-based route planning identified opportunities to shorten the existing travel paths. Taken together, these changes reduced the daily distance travelled by approximately 16.4 km, corresponding to an overall saving of about 5.2%. The magnitude of the reduction differed from one route to another, showing that the benefits of optimization depend strongly on the spatial and operational

characteristics of each collection route. Nevertheless, the results indicate that relatively small changes in route configuration can reduce unnecessary vehicle movement without reducing the level of collection service. Since the greatest distance saving was achieved for MON32, this route was selected as a representative example for comparing the existing and optimized configurations in Figure 3.

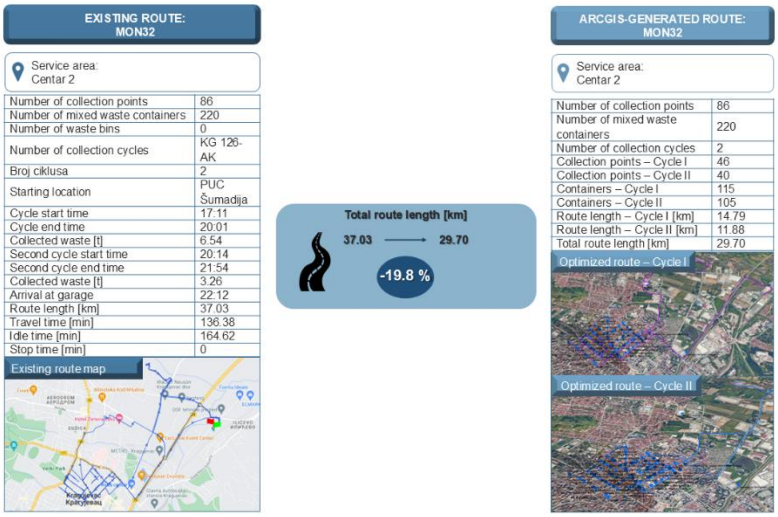


Figure 3 Comparison of the existing and ArcGIS-generated waste collection route (MON32)

Figure 3 illustrates the existing and optimized waste collection MON 32 route. The existing route serves 86 collection points with 220 mixed-waste containers and consists of two collection cycles. The recorded route length was 37.03 km. Following VRP-based route planning, the collection points and containers were distributed between two cycles, with 46 collection points and 115 containers assigned to the first cycle and 40 collection points and 105 containers to the second. The resulting route lengths were 14.79 km and 11.88 km, respectively. The optimized solution reduced the total route length to 29.70 km, corresponding to a distance saving of 7.33 km, or 19.81%, while maintaining the same number of collection points and containers.

These findings show that VRP-based route planning can reduce the distance travelled by waste collection vehicles while maintaining the required level of collection service. However, distance alone does not provide a complete picture of route performance. Routes differ not only in their length, but also in the amount of waste collected, the number of collection points served, travel time, and other operational characteristics. A route that is shorter is therefore not necessarily more efficient when the resources used and the service provided are considered together. To capture these differences, the analysis was extended by applying an input-oriented BCC DEA model under the assumption of VRS. Both the existing and optimized routes were evaluated to determine how efficiently operational inputs were used relative to the level of waste collection service provided. The resulting efficiency scores range from 0 to 1, with a score of 1 indicating a route located on the efficiency frontier, while values below 1 indicate different degrees of relative inefficiency. Figure 4 presents the efficiency scores obtained for the existing waste collection routes.

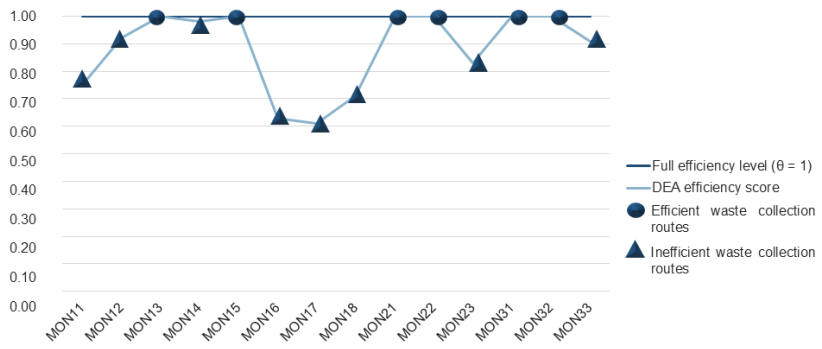


Figure 4 DEA efficiency scores of existing routes

The results show how much the inputs could be reduced while maintaining the same level of outputs, revealing clear differences in operational efficiency among routes within the same municipal collection system. It should be noted that routes MON14-MON18 were retained in the DEA analysis even though they were excluded from the subsequent optimization process. This distinction reflects the different purposes of the two methods. The VRP procedure implemented in Network Analyst was used to identify opportunities for spatial reorganization and distance reduction, which were limited for routes predominantly serving individual household bins. DEA, on the other hand, evaluates how efficiently each route uses its operational inputs relative to the collection service it provides. For this reason,

MON14-MON18 remained relevant decision-making units and were included when assessing the relative efficiency of the existing collection system. Their inclusion also provides a broader benchmark for comparing routes with different operational and service characteristics. The DEA results further support the importance of this distinction. Although routes MON14-MON18 offered limited scope for spatial route optimization, their efficiency was not necessarily high. In particular, MON16 and MON17 recorded some of the lowest efficiency scores in the analysed sample, while MON18 also remained below the efficiency frontier. This suggests that the absence of opportunities for further distance-based optimization should not be interpreted as evidence of overall operational efficiency. Inefficiency may instead arise from the relationship between travel time and distance on the input side and the amount of waste collected and number of collection points served on the output side. Table 3 compares the efficiency scores obtained for the existing and VRP-based route planning scenarios. The efficiency pattern changed only slightly after route optimization. Six routes (MON13, MON15, MON21, MON22, MON31, and MON32) recorded an efficiency score of 1.00 in both scenarios, meaning that they remained on the efficiency frontier. For most of the remaining routes, the differences between the two scenarios were relatively small.

Table 3 Scenario-specific DEA efficiency scores for existing and VRP-based route planning scenarios

Route	Existing - route frontier	Optimized - route frontier	Difference ($\Delta\theta_i$)	Trend
MON11	0.75	0.76	+0.010	↑
MON12	0.92	0.91	-0.010	↓
MON13	1.00	1.00	0.0000	→
MON14	0.98	0.98	0.00	→
MON15	1.00	1.00	0.000	→
MON16	0.63	0.63	0.000	→
MON17	0.61	0.63	+0.020	↑
MON18	0.71	0.71	0.000	→
MON21	1.00	1.00	0.000	→
MON22	1.00	1.00	0.000	→
MON23	0.83	0.81	-0.020	↓
MON31	1.00	1.00	0.000	→
MON32	1.00	1.00	0.000	→
MON33	0.91	0.89	-0.020	↓

Note: ↑ indicates an increase, → no change, and ↓ a decrease in relative DEA efficiency

Among the inefficient routes, MON11 showed a slight improvement, increasing from 0.75 to 0.76, while small decreases were observed for MON12 (0.92 to 0.91), MON23 (0.83 to 0.81), and MON33 (0.91 to 0.89). A lower DEA score after the optimization process does not necessarily mean that these routes became operationally worse. The VRP-based route planning primarily targets travel distance, whereas DEA considers the relationship between both inputs and the outputs. Moreover, since each scenario was evaluated against its own efficiency frontier, improvements achieved by other routes can influence the relative position of an individual DMU. The DEA results should be interpreted as changes in relative efficiency within each scenario rather than as a direct measure of the physical improvement achieved through optimization. An interesting result can be observed for MON17. This route was not modified during the optimization because it belongs to the group of routes predominantly serving individual household bins. Nevertheless, its DEA efficiency score increased from 0.61 to 0.63. This change does not reflect an improvement in the route itself, since its input and output values remained unchanged. Rather, it illustrates the relative nature of DEA. Because the existing and optimized scenarios were evaluated separately, differences in the performance of other routes affected the efficiency frontier and, consequently, the relative position of MON17 within the analysed set. In other words, a DEA score can change even when the characteristics of an individual route remain unchanged, if the reference environment against which it is evaluated changes. MON32 shows a different pattern, achieving the largest improvement through VRP-based route planning, with the route length reduced from 37.03 km to 29.70 km, resulting in a distance saving of 19.81%. Despite this substantial reduction, its DEA score remained at 1.00. MON32 was already located on the efficiency frontier before optimization and remained there afterward, since the improvement in route length could not produce a further increase in its DEA score beyond the maximum value of 1.00.

While this scenario-specific comparison is useful for understanding the relative efficiency of routes within each operational scenario, it does not allow the effect of route optimization to be measured directly. This is because the efficiency scores for the existing and optimized configurations are calculated against different efficiency frontiers. As a result, differences in θ may arise not only from changes in the individual routes, but also from changes in the frontier used as the benchmark. To overcome this limitation and provide a more direct and consistent comparison between the existing and optimized configurations, an additional DEA analysis using a common frontier was performed. Using a common frontier makes the efficiency scores directly comparable across the two scenarios. The results of the common-frontier DEA analysis are presented in Table 4, which reports the efficiency scores and corresponding input

reduction potentials for both the existing and optimized route configurations, together with the change in efficiency for each route.

Table 4 Common-frontier DEA efficiency scores for existing and alternative route configurations

Route	Existing efficiency - $\theta_{i,\ E}$	Existing input reduction potential	Optimized efficiency - $\theta_{i,O}$	Optimized input reduction potential	Difference - $\Delta\theta_i$	Trend
MON11	0.746	25.40%	0.746	25.40%	0.000	→
MON12	0.916	8.40%	0.903	9.70%	-0.013	↓
MON13	1.000	0.00%	1.000	0.00%	0.000	→
MON14	0.975	2.50%	0.975	2.50%	0.000	→
MON15	1.000	0.00%	1.000	0.00%	0.000	→
MON16	0.626	37.40%	0.626	37.40%	0.000	→
MON17	0.612	38.80%	0.612	38.80%	0.000	→
MON18	0.711	28.90%	0.711	28.90%	0.000	→
MON21	1.000	0.00%	1.000	0.00%	0.000	→
MON22	1.000	0.00%	1.000	0.00%	0.000	→
MON23	0.817	18.30%	0.801	19.90%	-0.016	↓
MON31	1.000	0.00%	1.000	0.00%	0.000	→
MON32	0.986	1.40%	1.000	0.00%	0.014	↑
MON33	0.895	10.50%	0.887	11.30%	-0.008	↓

Note: ↑ indicates an increase, → no change, and ↓ a decrease in relative DEA efficiency

The common-frontier analysis provides a clearer and more consistent basis for comparing the existing and optimized route configurations. As shown in Table 4, routes for which the input and output values remained unchanged also retained the same efficiency scores. An adequate example is MON17, with an efficiency score of 0.612 in both configurations. In the scenario-specific analysis (Table 3), however, its efficiency score increased from 0.61 to 0.63 despite no change in the route itself. This difference can therefore be attributed to the change in the reference frontier rather than to route optimization. By evaluating both configurations against the same frontier, the common-frontier analysis eliminates this benchmarking effect and allows changes in efficiency to be interpreted more directly.

The same pattern can be seen for the other routes that remained unchanged. MON11 retained an efficiency score of 0.746, while MON13 remained fully efficient at 1.000. No change was also observed for MON14, MON15, MON16, MON18, MON21, MON22 and MON31. This confirms that, when route characteristics remain unchanged, the common-frontier approach produces the same efficiency assessment for both configurations. Among the routes affected by optimization, the clearest improvement was observed for MON32. Its efficiency score increased from 0.986 to 1.000 ($\Delta\theta_i$ = +0.014), meaning that the optimized configuration reached the common efficiency frontier. This improvement coincided with a substantial reduction in route length, from 37.03 km to 29.70 km. Interestingly, this change was not visible in the scenario-specific analysis, where MON32 was classified as fully efficient under both separately estimated frontiers. However, a reduction in route distance did not necessarily lead to a higher DEA efficiency score. The efficiency score of MON12 decreased slightly from 0.916 to 0.903, while MON23 decreased from 0.817 to 0.801 and MON33 from 0.895 to 0.887. This can be explained by the multidimensional nature of the DEA model. Although route optimization primarily targeted travel distance, DEA evaluates route length and travel time simultaneously in relation to the outputs produced. A shorter route therefore does not automatically result in a higher efficiency score, as the final DEA assessment depends on the combined relationship between inputs and outputs.

Overall, the two DEA analyses provide complementary perspectives on route performance. While the scenario-specific analysis characterizes relative efficiency within each operational scenario, the common-frontier analysis provides a consistent benchmark for directly assessing efficiency changes associated with route optimization and is therefore used as the primary basis for evaluating its effects.

CONCLUSION

This study showed that combining VRP-based route planning with DEA provides a useful way to evaluate municipal waste collection from different perspectives. VRP-based route planning identified opportunities to reduce unnecessary travel, although the potential for improvement varied between routes. Among the analysed routes, MON32 showed the greatest reduction in distance, decreasing by 7.33 km (19.81%), while several existing routes

remained unchanged. The DEA results provided an additional perspective by showing that shorter routes are not necessarily more efficient when route length, travel time, collected waste, and the number of collection points are considered simultaneously. The scenario-specific analysis showed how the routes performed relative to one another within each operational scenario. The common-frontier analysis then allowed the existing and optimized routes to be assessed using the same benchmark. Under this comparison, MON32 improved from 0.986 to 1.000 and reached the efficiency frontier, while some routes became slightly less efficient despite reductions in travel distance. These findings highlight the value of combining VRP-based route planning with DEA rather than evaluating route performance based on travel distance alone.

The ArcGIS-generated route configurations should be interpreted as heuristic improvements over the recorded routes, as global optimality was not assessed in this study. The purpose of the routing stage was to generate a feasible alternative operational scenario for subsequent efficiency evaluation rather than to compare the performance of different optimization algorithms. A comparative evaluation of heuristic, metaheuristic, and exact solution approaches could therefore be considered in future research. Overall, the proposed approach can support more efficient route planning and resource use in municipal waste collection, while reductions in travel distance may also contribute to lower fuel consumption and associated operating costs. Future research could also broaden the assessment by incorporating environmental variables, particularly fuel consumption and related emissions. Their inclusion would require direct measurements for individual routes and would allow efficiency to be evaluated from both operational and environmental perspectives.

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