

Multi-objective vehicle routing optimisation for sustainable maintenance of urban parks: a case study of Sofia, Bulgaria

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Abstract

Regular maintenance of spatially distributed urban parks requires municipal vehicles and maintenance teams to travel between a central depot and multiple service locations. When these routes are planned manually, unnecessary travel may increase fuel consumption, operating costs and CO₂ emissions. The case study focuses on the planning of municipal park-maintenance trips in Sofia, Bulgaria. Seven large parks, served from one depot, were included in the analysis. Their service requirements and time windows were incorporated into a multi-objective vehicle routing model. The calculations also accounted for the length of the working day, travel costs, and the estimated CO₂ emissions of the diesel vehicles. The optimisation was implemented in Python using Google OR-Tools and compared with a manually planned baseline scenario. Under the tested scenario conditions, the optimised solution indicates an approximate 20 % reduction in total travel distance, travel time, fuel consumption, and CO₂ emissions. The number of active vehicles required for the selected daily maintenance tasks was also reduced from three to two. A standard vehicle routing approach was modified to reflect the operational and environmental aspects of municipal park maintenance. It may also be suitable for planning other municipal services, provided that the necessary local information is available.

Key words: carbon emissions, Google OR-Tools, municipal services, urban green infrastructure, vehicle routing problem.

Introduction

Urban green infrastructure (UGI), including parks, gardens and other green spaces, is a well-established component of sustainable urban planning and man-

agement (Mell 2008, Laforteza et al. 2009, Haq 2011, Demuzere et al. 2014, Hanna and Comín 2021, Korkou et al. 2023). These spaces regulate the urban microclimate, improve air quality, support biodiversity, and provide places for recre-

ation and social interaction. At the same time, the growing demand for high-quality green spaces presents municipal administrations with serious challenges arising from rapid urbanisation and public funding constraints, which necessitate more effective management and maintenance strategies.

Green urban areas are commonly serviced according to fixed schedules, and their maintenance requires repeated movement of vehicles and teams between spatially distributed locations. In Sofia case study, manual geographical grouping may produce overlapping or unnecessarily long routes, with corresponding use of resources and generation of emissions. Cities can improve these practices by applying optimisation methods that support more efficient resource allocation while contributing to sustainability objectives (Bibri and Krogstie 2017). Time restrictions are common in the planning of logistics and transport operations. Routing under such conditions is commonly examined through the vehicle routing problem with time windows (VRPTW) (Crainic et al. 2009, Toth and Vigo 2014, Savelsbergh and Van Woensel 2016, Moghdani et al. 2021). However, it has received limited attention in relation to green infrastructure maintenance, where time windows, heterogeneous job types and environmental objectives must be considered simultaneously.

Efficient maintenance logistics directly affects the quality, accessibility, and ecological functioning of urban green infrastructure. Poorly planned maintenance routes may increase emissions and operating costs, while also reducing the capacity of municipal services to maintain parks in good ecological and recreational condition. For this reason, route optimisation should be considered part of sustainable

urban green infrastructure management, not only as a transport planning problem.

This study examines the use of multi-objective route optimisation in planning municipal park-maintenance activities in Sofia, Bulgaria. The analysis covers travel distance, time spent at each site, service time windows, daily working-time limits, transport costs, and the estimated CO₂ emissions from diesel maintenance vehicles.

The novelty of the study lies in adapting a standard VRPTW approach to the specific conditions of municipal park maintenance in a medium-sized Eastern European city. In this setting, routing decisions are not assessed only by distance or cost, but also by service feasibility and estimated environmental impact. This is important because maintenance operations should support the ecological functions of urban parks rather than generate avoidable vehicle movement and emissions around them.

Materials and Methods

Study area

The study covers the territory of Sofia Municipality. The analysis includes one central depot, managed by Sofia Inspectorate, and seven major city parks: Borisova Gradina, South Park, West Park, North Park, Geo Milev Park, Ovcha Kupel Park, and Druzhba Park. These sites were selected because they represent large and regularly maintained green areas located in different parts of the city. Their coordinates, approximate areas, service times, and time windows are summarised in Table 1.

The geographical coordinates were obtained from OpenStreetMap (Open-

Table 1. Park locations and service parameters.

Park	Latitude	Longitude	Area, ha	Time window	Service time, h
Depot	42°41'52" N	23°19'19" E	-	8:00–16:00	-
Borisova Gradina	42°40'40" N	23°20'25" E	120	8:00–12:00	2.0
South Park	42°40'24" N	23°19'06" E	85	8:00–11:30	1.5
West Park	42°42'11" N	23°16'56" E	53	8:30–12:00	1.3
North Park	42°43'57" N	23°18'47" E	50	9:00–15:00	1.2
Geo Milev Park	42°40'59" N	23°21'07" E	30	8:30–13:30	1.0
Ovcha Kupel Park	42°40'55" N	23°16'04" E	24	9:00–15:00	0.8
Druzhba Park	42°40'27" N	23°24'22" E	20	8:00–12:30	0.7

StreetMap Contributors 2023) and checked against municipal information (Sofia Municipality 2023).

The parks are located in the Sofia Valley, a lowland area characterised by predominantly flat terrain and Fluvisols. Several small rivers characterise the city's hydrography, and the main vegetation consists of broad-leaved deciduous trees and managed lawns.

Data

The input dataset included park coordinates, service times, time windows, travel distances, travel times, vehicle availability, fuel consumption, and the emission factor for diesel vehicles. Distance and driving-time data between all locations, including the central depot and the selected parks, were obtained using the Google Maps Directions API (Google LLC 2023b). The data used in the analysis were compiled in January 2026, with the spatial and routing data retrieved on 15 January 2026. The same distance and travel-time matrix was used for both the manually planned baseline scenario and the optimised routing scenario. This ensured that the two scenarios were compared under identical spatial and travel-time assumptions.

The municipal fleet was represented by three diesel vehicles, each with a daily

working-time limit of 8 h. Fuel consumption was assumed to be $0.25 \text{ L} \cdot \text{km}^{-1}$, and CO_2 emissions were calculated using an emission factor of $2.64 \text{ kg} \cdot \text{L}^{-1}$ (European Commission 2014). All financial calculations were performed in EUR, using an exchange rate of 1.95583 BGN per EUR.

Vehicle load capacity was not included as a limiting constraint. This assumption is justified because the analysed task concerns municipal park maintenance visits rather than the transport of large quantities of goods. The main operational constraints are therefore related to travel distance, service time, time windows, depot return, and daily working time.

The overall research workflow adopted in this study is presented in Figure 1.

The framework includes spatial data collection, GIS processing, distance matrix generation, baseline scenario construction, mathematical model formulation, multi-objective optimisation using Google OR-Tools and results evaluation. The methodology enables systematic evaluation of operational efficiency and environmental performance in urban park maintenance routing.

Baseline routing scenario

The baseline is an author-constructed planning scenario and is not derived from

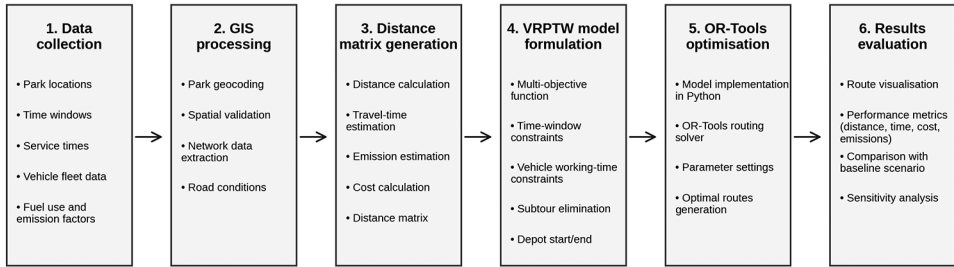


Fig. 1. Research workflow of the multi-objective VRPTW optimisation framework for urban park maintenance routing.

historical GPS traces or recorded municipal vehicle routes. It was prepared to represent conventional manual planning of municipal park maintenance. The seven parks were assigned to the three available diesel vehicles by geographical proximity, while observing the park time windows, the specified service durations and the 8 h daily working-time limit. Route order was selected manually rather than by an optimisation algorithm. The baseline therefore provides a consistent reference scenario, but it should not be interpreted as a record of actual municipal operations.

The same distance matrix, travel-time assumptions, fuel consumption coefficient, and emission factor were used for both the baseline and optimised scenarios. This makes the comparison consistent because the observed differences between the two scenarios result from the routing logic rather than from different input data.

The baseline scenario reflects a practical planning situation in which routes are arranged manually and mainly by location. Such an approach can be feasible for daily work, but it may create repeated travel, uneven use of vehicles, and unnecessary overlap between routes. For this reason, it provides a suitable reference point for assessing whether algorithmic route optimisation can improve municipal park maintenance planning.

Mathematical model

The daily planning problem was formulated as a multi-objective vehicle routing problem with time windows. The formulation covers one depot, the selected park locations, and the available diesel-vehicle fleet. Its aim is to identify feasible routes while taking account of transport costs, travel time, and estimated CO₂ emissions. At the same time, the routes must respect the main operational constraints of the service: park service duration, depot departure and return, vehicle flow balance, time windows, possible waiting time, and the daily working-time limit.

The formulation reflects the organisation of daily municipal maintenance work. The parks form the routing nodes, the distances between them define the travel network, and the available vehicles make up the fleet. Each maintenance team may work for no more than 8 h per day. The daily working-time limit includes travel time, service time at the parks, any waiting required by the time windows, and the final journey back to the depot. Each park is visited once and within its specified time window. A vehicle leaves the central depot, may serve several parks in succession, and returns after its final assigned visit. It is not required to return to the depot between two consecutive park visits.

Let $N = \{0, 1, \dots, n\}$ be the set of nodes,

where node d denotes the depot. Let P be the set of park nodes and let K be the set of available vehicles. For each arc (i, j) , d_{ij} denotes travel distance, t_{ij} denotes travel time, and c_{ij} denotes transport cost. Each park i has a service time s_i and a time window $[a_i, b_i]$, where a_i is the earliest allowed service start time and b_i is the latest allowed service start time. The depot is the starting and ending point of each route, and $H = 8$ h denotes the maximum permitted daily working time of each vehicle.

The binary decision variable x_{ijk} takes value 1 if vehicle k travels directly from node i to node j , and 0 otherwise. The binary variable y_{ik} takes value 1 if park i is served by vehicle k , and 0 otherwise. The variable T_{ik} denotes the service start time of vehicle k at park i . The variable A_{ik} denotes the arrival time, and W_{ik} denotes the waiting time between arrival and the beginning of service.

CO₂ emissions for each route segment are calculated according to Equation (1):

$$e_{ij} = d_{ij} \cdot f \cdot EF \quad (1)$$

where:

- d_{ij} denotes the travel distance between nodes i and j in km;
- f is the assumed fuel consumption of the maintenance vehicles, equal to 0.25 L·km⁻¹;
- EF is the diesel emission factor, equal to 2.64 kg·L⁻¹.

The multi-objective function is expressed through a weighted-sum formulation (Marler and Arora 2004). To keep the notation clear, the normalised cost, time, and emission components are first defined by equations (2) – (4):

$$C_N = (\sum_{k \in K} \cdot \sum_{i \in N} \cdot \sum_{j \in N, j \neq i} \cdot c_{ij} \cdot x_{ijk}) \cdot C_{\max}^{-1}, \quad (2)$$

$$T_N = (\sum_{k \in K} \cdot \sum_{i \in N} \cdot \sum_{j \in N, j \neq i} \cdot t_{ij} \cdot x_{ijk}) \cdot T_{\max}^{-1}, \quad (3)$$

$$E_N = (\sum_{k \in K} \cdot \sum_{i \in N} \cdot \sum_{j \in N, j \neq i} \cdot e_{ij} \cdot x_{ijk}) \cdot E_{\max}^{-1}. \quad (4)$$

The objective function is then written as Equation (5):

$$Z_{\min} = \alpha_1 \cdot C_N + \alpha_2 \cdot T_N + \alpha_3 \cdot E_N, \quad (5)$$

where: α_1 , α_2 , and α_3 are non-negative weighting coefficients for transport cost, travel time, and CO₂ emissions, respectively.

The weights are normalised according to Equation (6):

$$\alpha_1 + \alpha_2 + \alpha_3 = 1 \quad (6)$$

The terms $C_{\max}$, $T_{\max}$, and $E_{\max}$ are normalisation constants used to make the three objective components comparable.

Several operational constraints were incorporated into the model to guarantee feasible daily routes.

Each park must be assigned to exactly one vehicle, as expressed by Constraint (7):

$$\sum_{k \in K} y_{ik} = 1, \forall i \in P. \quad (7)$$

The assignment variable is linked to the routing variable as specified by Constraint (8):

$$\sum_{j \in N, j \neq i} x_{ijk} = y_{ik}, \forall i \in P, k \in K. \quad (8)$$

Flow conservation is required at each park node. If a vehicle enters a park, it must also leave it, as described by Constraint (9):

$$\sum_{j \in N, j \neq i} x_{ijk} = \sum_{j \in N, j \neq i} x_{jik}, \forall i \in P, k \in K. \quad (9)$$

Each active vehicle route must start from the depot, as required by Constraint (10):

$$\sum_{j \in P} \cdot x_{0jk} \leq 1, \forall k \in K. \quad (10)$$

Each active vehicle route must return to the depot, as required by Constraint (11):

$$\sum_{i \in P} \cdot x_{i0k} \leq 1, \forall k \in K. \quad (11)$$

The number of departures from the depot must equal the number of returns for each vehicle, as imposed by Constraint (12):

$$\sum_{j \in P} \cdot x_{0jk} = \sum_{i \in P} \cdot x_{i0k}, \forall k \in K. \quad (12)$$

The service at each park must start within the predefined time window, as specified by Constraint (13):

$$a_i \leq T_{ik} \leq b_i, \forall i \in P, k \in K, y_{ik} = 1. \quad (13)$$

If a vehicle arrives before the beginning of the allowed time window, it may wait until service is permitted to begin. Waiting time is non-negative and may occur only when park i is assigned to vehicle k , as specified by Constraint (14):

$$0 \leq W_{ik} \leq My_{ik}, \forall i \in P, k \in K. \quad (14)$$

The service start time equals the arrival time plus any waiting time before service begins, as expressed by Constraint (15):

$$T_{ik} = A_{ik} + W_{ik}, \forall i \in P, k \in K. \quad (15)$$

Chronological sequencing between consecutive visits is imposed using the Big-M approach, as expressed in Equation (16).

$$T_{jk} \geq T_{ik} + s_i + t_{ij} - M(1 - x_{ijk}), \quad (16)$$

$$\forall i, j \in N, i \neq j, k \in K,$$

where:

- T_{ik} and T_{jk} are the service start times of vehicle k at nodes i and j , respectively;
- M is a sufficiently large positive constant.

In this study, M is defined by Equation (17):

$$M = H + \max(s_i) + \max(t_{ij}), \quad (17)$$

where:

- $H = 8$ h is the daily working-time horizon;
- $\max(s_i)$ is the maximum service time; and
- $\max(t_{ij})$ is the maximum travel time between two nodes.

This value is large enough to deactivate the sequencing constraint when arc (i, j) is not used, while remaining limited enough to avoid unnecessary numerical instability.

The total daily working time of each vehicle includes travel time, service time, waiting time, and the final journey back to the depot. It is limited by Constraint (18):

$$\begin{aligned} & \sum_{i \in N} \cdot \sum_{j \in N, j \neq i} \cdot t_{ij} \cdot x_{ijk} + \\ & + \sum_{i \in P} \cdot s_i \cdot y_{ik} + \sum_{i \in P} \cdot W_{ik} \leq (18) \\ & \leq H, \forall k \in K. \end{aligned}$$

The travel-time term includes all arcs used by the vehicle, including the initial departure from the depot and the final return to the depot. Therefore, Constraint (18) covers the complete daily route duration.

The routing variable is defined by Constraint (19):

$$x_{ijk} \in \{0,1\}, \forall i, j \in N, i \neq j, k \in K. \quad (19)$$

The assignment variable is defined by Constraint (20):

$$y_{ik} \in \{0,1\}, \forall i \in P, k \in K. \quad (20)$$

The mathematical formulation brings routing, scheduling, and environmental aspects into one optimisation model. The constraints define the basic logic of the routing problem. Each park has to be visited once, vehicle flow must be balanced

at every visited node, and each active route must start and finish at the depot. The model also accounts for service time windows and permits a vehicle to wait when it arrives before the beginning of an allowed service period. The total daily working time of each vehicle is limited to 8 h and includes travel time, service time, waiting time, and the final return journey to the depot.

The mathematical formulation presents the analytical structure of the VRPTW model. In the computational implementation, Google OR-Tools was used to handle the routing search, time-window feasibility, waiting time, route sequencing, depot return, and vehicle working-time limits through its internal routing and time-dimension mechanisms. Thus, the equations define the modelling logic of the problem, while OR-Tools provides the operational implementation of the full routing procedure.

Reproducibility and implementation details

The optimisation model was implemented in Python using the Google OR-Tools library (Google LLC 2023a). OR-Tools was selected because it provides established routing solvers for vehicle routing problems with time windows and allows the use of routing dimensions for time-window feasibility, waiting time, depot return, and vehicle working-time limits.

The same input dataset was used across all experimental scenarios. The model settings were kept constant across the different weighting scenarios, while only the weighting coefficients in the objective function were changed. This allowed the effect of different economic and environmental optimisation priorities to be examined under comparable con-

ditions. For the cost–emission trade-off analysis, the tested weighting scenarios used $w = 0.0, 0.2, 0.4, 0.6, 0.8, 0.9$, and 1.0 . The parameter indicates the relative emphasis placed on the economic and environmental objectives in each scenario. All other model settings and operational constraints remained unchanged across the tested scenarios.

OR-Tools was used to generate feasible initial routes and improve them through local search. In the computational implementation, the time dimension was used to represent travel time, service time, time windows, possible waiting time, and the daily working-time horizon. This ensures that the generated routes are not only shorter or less costly, but also feasible within the operational constraints of municipal park maintenance.

Methodological contribution

The study does not introduce a new routing algorithm. Its methodological contribution is the transparent comparison of an author-constructed manual scenario with feasible optimised routes based on the same input assumptions. This allows operational feasibility and estimated environmental performance to be examined together in the planning of municipal green infrastructure maintenance.

The framework may also be adapted to other spatially distributed municipal services, provided that service times, time windows, fleet availability, and locally validated route data are available.

Limitations of the model

The study has several practical limitations. First, the optimisation model is static. It does not include real-time changes in traffic, temporary road closures, accidents, or

unexpected delays. Since traffic intensity in Sofia varies during the day, actual travel time and fuel consumption may differ from the values used in the model.

Second, fuel use and CO₂ emissions were calculated from assumed diesel consumption and standard emission factors. These estimates may vary in practice depending on vehicle condition, driving behaviour, weather, road conditions, and the number of stops.

Third, the case study is limited to one city, seven park locations, and a small municipal fleet. The results show the practical potential of the model, but larger urban systems would require recalibration of the parameters, including fleet size, traffic conditions, service area, and maintenance schedule.

Another limitation is related to the baseline scenario, which was prepared by the authors and was not based on historical municipal route records. The estimated improvement therefore depends on how this reference scenario was defined. Accordingly, the reduction of approximately 20 % applies to the scenarios compared in this study and should not be interpreted as an effect that can be expected in every operational setting.

Future improvements may include real-time traffic data, dynamic route adjustment, electric or hybrid municipal vehicles, and additional environmental indicators such as NO_x emissions, particulate matter, and noise pollution (Taniguchi and Thompson 2014, Perboli et al. 2018).

Results

Aggregate comparison of routing scenarios

The manually planned baseline and the optimised VRPTW scenario were com-

pared using aggregate operational and environmental indicators. Both scenarios included the same central depot, seven park locations, service durations, time windows, vehicle characteristics, and the same 8 h daily working-time limit. The baseline was constructed by the authors using manual geographical grouping and three available vehicles, whereas the optimised scenario was generated using the VRPTW framework.

Because the available route-level output does not permit reliable reconstruction of the individual vehicle trajectories, Figure 2 presents the comparison at the aggregate scenario level. It does not depict the exact sequence of park visits or the individual paths followed by each vehicle. Intermediate returns to the depot between consecutive park visits are not mandatory in the model.

Under the assumptions used in the analysis, the number of vehicles in operation fell from three in the manual scenario to two in the optimised scenario. The corresponding daily travel distances were 40.0 and 32.0 km. All seven scheduled park visits were retained. Fuel consumption and CO₂ emissions were calculated from these distances, using the same consumption and emission coefficients for both scenarios.

Cost-emission trade-off under different weighting scenarios

Figure 3 illustrates the trade-off between operational cost and CO₂ emissions under different weighting scenarios.

The trade-off curve shows that lower CO₂ emissions are associated with higher operational cost across the tested weighting scenarios. Beyond a certain point, further improvements in environmental performance require disproportionately high

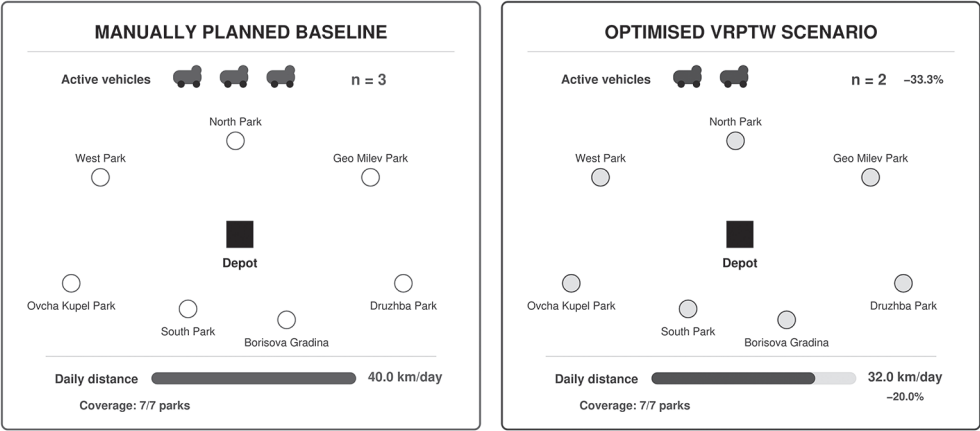


Fig. 2. Aggregate comparison of the manually planned baseline and the optimised VRPTW scenario.

Note: Park symbols show coverage of all seven maintenance locations but do not indicate actual routes or visit order; distances are aggregate scenario outputs.

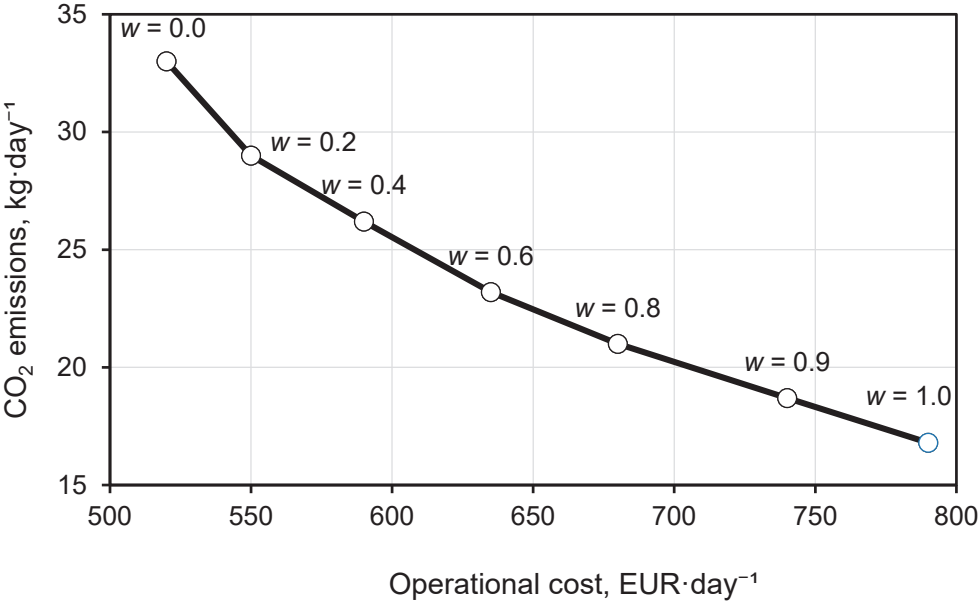


Fig. 3. Trade-off between operational cost and CO₂ emissions under different optimisation weighting scenarios.

Note: w denotes the weighting parameter varied across the optimisation scenarios to change the relative emphasis between the economic and environmental objectives, where $0 \leq w \leq 1$.

operational costs. This trade-off between economic and environmental objectives has been reported in previous studies on vehicle routing problems (Savelsbergh and Van Woensel 2016).

Operational and environmental performance

To evaluate the practical effect of the optimisation model, the optimised VRPTW solution was compared with the manually planned baseline scenario described in the methodology. The same input data and calculation assumptions were used for both scenarios. The key indicators are presented in Table 2.

The results in Table 2 are planning-level estimates based on the selected routing assumptions. Compared with the baseline, the optimised scenario reduced total daily travel distance by 8.0 km, or 20.0 %, and required fewer active vehicles for the same maintenance tasks. Fuel consumption and CO₂ emissions were calculated from the respective travel distances using the same assumed coefficients in both scenarios. The reported values therefore indicate the potential effect of route optimisation under the conditions of the study and should not be interpreted as savings measured in municipal operations.

Before practical implementation, the

model should be tested using dynamic traffic data, seasonal maintenance schedules, and real operational records.

Annual impact projection

The annual effect of the optimised routing was estimated by extrapolating the daily scenario results in Table 2 over 250 working days per year, assuming an 8 h working day. Under these assumptions, the daily reduction of 8 km corresponds to approximately 2000 km of avoided travel per year. Applying the assumed fuel consumption of 0.25 L·km⁻¹ and the diesel emission factor of 2.64 kg·L⁻¹ gives scenario-based annual savings of approximately 500 L of diesel fuel and 1.32 t of CO₂ emissions.

Similar scenario-based estimates are commonly used in urban service and transport planning to assess the potential operational and environmental benefit of route optimisation (Taniguchi and Thompson 2014, Russo and Comi 2016).

These values should be interpreted as scenario-based estimates, not as measured annual savings. They show the potential effect of optimised routing under the selected assumptions. Actual results would depend on traffic conditions, seasonal maintenance schedules, vehicle condition, driving behaviour, and the number of service days.

Table 2. Comparison of manual and optimised routing performance.

Indicator	Manual routing	Optimised routing	Improvement, %
Daily distance, km	40.0	32.0	20.0
Daily travel time, h	2.5	2.0	20.0
Daily fuel consumption, L	10.0	8.0	20.0
Daily CO ₂ emissions, kg	26.4	21.1	20.0
Active vehicles, number	3.0	2.0	33.3

Source: Authors' calculations based on park service parameters, distance and travel-time matrix, fuel consumption coefficient and optimisation results generated using Google OR-Tools.

Discussion

The results show that multi-objective routing can improve the planning of municipal park maintenance when operational and environmental criteria are considered together. The benefits of the model are not limited to reducing travel distance. It also improves the coordination of daily maintenance routes, reduces repeated vehicle movement, and allows the same set of parks to be serviced with fewer active vehicles under the tested scenario conditions. This finding is consistent with the broader literature on urban service routing, in which route optimisation is used to reduce travel distance, fuel consumption and emissions in spatially distributed service systems (Russo and Comi 2016, Savelsbergh and Van Woensel 2016). The present study applies this principle to municipal park maintenance rather than to conventional freight distribution. Park maintenance combines spatially distributed service locations, fixed working-time limits, service duration at each park and environmental sensitivity around green areas. The model therefore extends transport-planning methods to the management of urban green infrastructure.

Another limitation is related to computational complexity. Vehicle routing problems with time windows are demanding even when the number of service points is not large. In this study, only seven parks were included, but the number of possible route combinations still increases when several vehicles, time windows, service durations, and different objective weights are considered. Google OR-Tools found feasible solutions for all tested scenarios. However, these results should not be read as a universally optimal policy for municipal maintenance planning. If the model is applied to a larger urban system, it should be tested further through repeated runs,

sensitivity analysis, and comparison with real operational records.

Conclusions

This study proposed a multi-objective vehicle routing model with time windows for the planning of municipal park maintenance in Sofia, Bulgaria. The model does not treat routing only as a problem of reducing distance. It also reflects the daily conditions under which park maintenance is carried out. For this purpose, service times, time windows, working-time limits, travel distance, transport cost, and estimated CO₂ emissions were considered within a single planning framework.

The optimised routing scenario indicated an approximate 20 % reduction in daily travel distance, travel time, fuel consumption, and CO₂ emissions compared with the manually planned baseline scenario. Under the tested scenario conditions, the number of active vehicles required for the selected maintenance tasks was also reduced from three to two. These results show that route optimisation can support more efficient and environmentally responsible municipal park maintenance.

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