Multi-objective modelling of a roadside mowing problem: a case study in France

Abstract— Roadside maintenance is a significant challenge for many territories worldwide. For safety reasons, these roadsides have to be maintained regularly, which has a substantial economic impact requiring a significant investment of staff and material. This paper addresses the problem of planning optimal trajectories of mowing machines within a dedicated territory in order to meet several objective criteria such as: minimising the travel distance, the number of mowing machines, as well as minimising the time and the cost associated with each yearly operation. Firstly, we define the mathematical methodology of the multi-objective criteria that we need to calculate. Secondly, we propose a clustering approach based on the k-means algorithm in order to identify the best sub-sectors of road sections that each technical centre needs to plan in order and maintain using existing equipment. Thirdly, we apply an optimal routing between each cluster based on TomTom API routing and identify the distance used to formulate our multi-objective optimisation criteria to minimise the cost and the use time associated with various mowing scenarios. Finally, we analyse the best setup to satisfy all criteria in the current case study area and present future projections of a local versus global optimisation approach.

Keywords—Mowing, multi-objective, road maintenance, k-means, road segmentation, optimal routing.

I. INTRODUCTION

The relationship between road infrastructure and economic development is widely studied as 25 million kilometres of new roads will be built by 2050 [1]. The vegetated strips of land located near roads that separate them from the surrounding landscape called roadside or road verges [2] are affected by this growth in road infrastructure. Roadside consists of the entire public road domain except for the pavement and the rugged roadside. In France, the roadside represents about 5,000 km^2 and is thought to be the largest wilderness area compared to the 3,450 km^2 of the six national parks [3]. Roadsides are a social interface between forests, wildlife, agricultural farms, rural communities, vehicles, communication networks, landscape, and many other aspects [4]. As a result, they are receiving increasing attention within territories and the scientific literature to regularly maintain them sustainably.

In order to preserve the safety of the drivers and to maintain the road annexes in good condition, roadside maintenance is a necessary activity that councils need to undertake every year. The maintenance of these structures includes mainly mowing and pruning, alongside other controlled interventions for regular maintenance when needed [5]. The maintenance of roadsides integrates several issues with various aspects: (i) **economic** (e.g. continuous investment in the maintenance equipment, the attractiveness of the territories linked to the quality of the maintained landscape), (ii) **technological** (e.g. the biomass valorisation, the reduction of the carbon footprint), (iii) **social** (e.g. road safety, flood and fire prevention) and (iv) **environmental** (e.g. the preservation of the biodiversity, the water improvement, the air and soil quality, etc.).

In France, mowing is the main annual roadsides maintenance activity and must be carried out in a limited time with the human and material resources available. Therefore, optimal road mowing is a significant challenge for territories, which requires a large budget and detailed annual maintenance in terms of staff and mowing devices; making informed decisions regarding the staff requires a minimum distance that needs to be delivered in a limited amount of time to represent crucial factors that need a data-driven decision-making modelling approach.

This paper addresses the problem of planning optimal trajectories of mowing machines within a dedicated territory to minimise costs, travel time, and the number of machines required to complete the operations. To the best of our knowledge, this work is a pioneering work aiming at solving the mowing and routing issue given specific constraints by proposing a combination of machine learning clustering techniques [6], together with optimal routing and multi-objective optimisation problem-solving. Section II presents a dedicated literature review on the topic, followed by our proposed Methodology in Section III. In Section IV, we present the results of a local clustering and optimisation approach applied to the Neufchateau Technical Centre in eastern France before ending with Conclusions, limitations and future perspectives for our work in Section V.

II. LITERATURE REVIEW

Road infrastructure act like a "barrier effect", leading to the fragmentation of space, thus disrupting the movement of species and causing the isolation of habitats [19]–[22]. Roadsides, also known as the road verges, are part of the road right-of-way with the exception of pavements and the hard shoulder. They are part of the definition of green corridors of ecological continuity because of their size and the fact that they are contiguous with other spaces: urban, agricultural and forest ecosystems [2]. In a perspective of reducing maintenance costs, it seems relevant to address the optimisation of roadside maintenance sites, especially on the mowing roadside optimisation. However, it is worthy to note that there is poor literature on this field. Most of the optimisation fields related to the road management and maintenance problem are waste allocation problems [7]–[11], human resource allocation [12], allocating resources [13], [16], highway maintenance [14], [15], winter road maintenance [17], pavement and bridge maintenance [18], TABLE 1 presents a summary of these most recent works. They address several optimization approaches ranging from linear programming to Mixed-Integer Programming (MIP), etc.

TABLE 1. SUMMARY OF LITERATURE REVIEW ON THE ROADSIDE MOWING OPTIMISATION PROBLEMS.

Problem	Objective	Model	Method	Reference
The location problem of treatment and service facilities in municipal solid waste (MSW) management system	Development of sophisticated decision support tools for planning MSW management system in an economic-efficient and environmental	Mixed integer programming (MIP) model	Lingo software	[7]
Waste allocation problem	Balancing the overall system costs, environmental impact and waste of resources	Multi-objective nonlinear programming	Dynamic programming	[8]–[10]
Municipal solid waste (MSW) management	Locating the optimal sites of MSW recycling and disposal facilities, optimising the capacity allocation of landfills	MIP model	GAMS software	[11]
Human resource allocation for traffic management	Minimising the cost, CO2, staff personnel Maximising the segment allocation	A two-phase fuzzy binary programming model	Two-phase MIP programming method	[12]
Allocating resources to roadside incidents	Minimising cost and time	Linear programming	Heuristic approach	[13]
Highway maintenance	Maximise highway lifecycle	Markovian model for maximising highway lifecycle	A genetic algorithm combining with Markovian approach	[14], [15]
Calculating and analysing a numerical risk factor of a road.	Optimising the resource allocation	Quantitative calculation of safety level	Cost-benefit analysis	[16]
Winter road maintenance problem	Proposing a framework for winter road maintenance problems	MIP model	Metaheuristic algorithms	[17]
Pavement and bridge management problems	Allocation of cost	Multi-period Linear programming	Markov stable solution	[18]

Very few of these have relied on the benefits of machine learning techniques in order to combine traditional optimisation techniques with data-driven approaches.

Among all forms of artificial intelligence, machine learning attempts to extract patterns from large data sets, usually in the form of an algorithm and attempts to predict an outcome [23]. These learning methods can be supervised [24] or unsupervised, as is the case with cluster analysis. The latter aims at grouping similar objects in different clusters and can be used to identify patterns to provide predictions about the database structure [6]. Among these clustering methods, the non-hierarchical clustering method considers that the similarity between a pair of objects is defined by their distance [6]. It consists in creating distinct groups (portions of the road network) in which the entities of the same group have similar properties. It finds clusters such that objects within each cluster are as close to each other as possible [25]. This approach is interesting for our problem because it aims to find patterns in a dataset and value the homogeneity of the objects in the system [26]. This involves grouping roads based on their common characteristics to facilitate optimisation of roadsides maintenance activities.

As a summary, our work brings an innovative approach towards the integration of traditional multi-objective optimisation with a clustering unsupervised machine learning approach in order to minimise several objectives as defined in the next section around the proposed methodology.

III. METHODOLOGY

Section III presents the overall methodology we propose, which is composed of three main steps: a) area mapping, filtering of dedicated road segments falling under the management of the Vosges department in East France, as well as their category, length, etc., b) a clustering approach based on the k-means unsupervised algorithm, followed by c) optimisation of mowing routes based on TomTom API for shortest path estimation between each identified cluster. These are further detailed as follows.

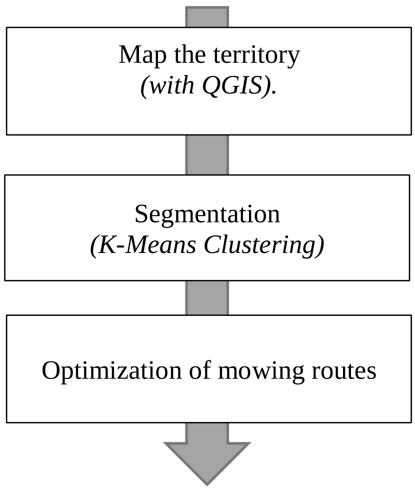

Fig 1. Proposed Methodology for Roadside Mowing Optimization

A. Mapping and Filtering

To preserve the safety of road users and to keep the road in good condition, roadsides need to be mowed annually. Unfortunately, mowing requires significant human, financial and material resources for the territories in charge. To carry out this study, the case of the Vosges department located in the North East of France was analyzed (Fig. 2).

Fig 2. Location of our case study

The department is characterized by two distinct geographies. The western part of the department consists of hills with a deciduous cover, while the mountainous eastern part is covered with coniferous forests. This difference in the geography of the department leads to different maintenance practices of the roadsides, as the grass does not grow differently depending on the altitude. In order to facilitate management and maintenance, the department is divided into 16 cantons (or zones $Z_i^{TC_i}$). Each canton has a technical center (TC_i) who is in charge of the maintenance activities of the territory, including mowing of the roadsides (Fig. 3).

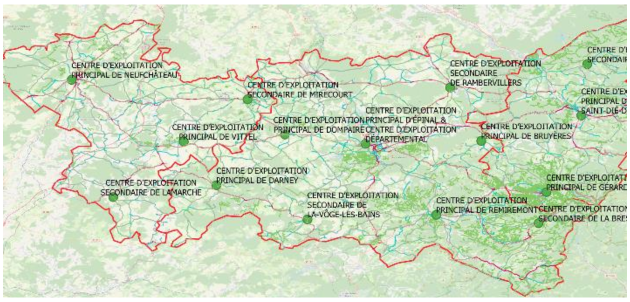

Fig. 3 Location of the technical centers in the Vosges territory

The organization of work sites depends on several factors: the type of road, the human and material resources available, the growth of vegetation, and the weather. An optimization problem can only act on the route taken by the construction site to maintain the roadsides and on the resources available.

A mowing site is mobile, meaning that it moves along the road network to maintain the vegetation. It usually consists of a work team, a mowing machine and a safety vehicle. The route of the work site is planned in advance in order to give priority to the maintenance of risk areas. To define them, the territory classified its road into three types of roads according to their daily traffic: primary, secondary and tertiary. Overall, there are two mowing seasons per year, which are both considered in the current modeling approach.

B. Mathematical definitions

In order to help define the optimization problem, we start by defining the list of all required variables, as detailed in TABLE 2, and consecutively in each of the following sections.

TABLE 2. LIST OF BASELINE VARIABLES OF THE NETWORK.

Variable [unit]	Description
N=16	Total number of Technical centers
$\mathbf{TC_{i=\{1..N\}}}$ **[X, Y]**	Technical centers and their geo-location coordinates
$\mathbf{N_z}$	Total number of zones (cantons) in the Vosges area
$\mathbf{Z_i^{TC_i}}$	The zone areas allocated to each $\mathbf{TC_i}$
$\mathbf{NR_{Z_i}^{i}}$	The number of roads in each zone $\mathbf{Z_i}$ (includes primary, secondary and tertiary for this study)
$\mathbf{m} \in \{\mathbf{1...M_{TC_i}}\}$	Number of machines operating in each $\mathbf{TC_i}$
$\mathbf{u_m^{TC_i}}$[days]	Use time for machines in each $\mathbf{TC_i}$
$\mathbf{C_s^{TC_i}}$[€]	Cost of staff personnel for each $\mathbf{TC_i}$
$\mathbf{C_M^{TC_i}}$[€]	Cost of machines for each $\mathbf{TC_i}$

Each technical center in the Vosges $\boldsymbol{TC_i}$ is equipped with a number of machines $\boldsymbol{m} \in \{\mathbf{1...}\boldsymbol{M_{TC_i}}\}$ which are used to mowe twice per year the allocated number of roads $\boldsymbol{NR_{Z_i}^{i}}$. As an observation in this study, we treat all road types for each center equally, while a future detailed analysis is carried out in our upcoming work, based on the road type in use (primary, secondary or tertiary). Each center is characterized by the cost of the staff personnel needed to conduct the yearly operations, as well as the time required so far under the actual setup. In order to be able to optimize and prioritize the mowing of each zone, we proposed to firstly conduct a road data-driven clustering approach for each center in order to rank and minimize the total distance needed to mowe each zone.

C. Road segmentation clustering

Roads in a transport network have different features, mostly defined by the environmental area in which they are found; in order to be able to plan operations, we propose a data-driven clustering approach which groups road segments with similar features in the same class in order to be mowed together at the same time and avoid multiple back-and-forth between the $\boldsymbol{TC_i}$ and each road in the network.

The K-means method is a non-hierarchical clustering technique that groups the dataset into k sets and minimizes the sum of the distances between a data point and the nearest centroid [27]. Based on the distance metric specified, the algorithm tries to group the input data into various clusters. In our case, the road segments are objects to be clustered around centroids $C_i, \forall\, i = \{1..K\}$ which are obtained by minimizing the objective function:

$$V = \sum_{i=1}^{K} \sum_{x_j \to S_i} \left(x_j - \mu_i\right)^2, \quad (1)$$

where K is the total number of clusters, S_i (i = {1.. K}) represents the collection of distances between all the road segments in a cluster i ($x_j \rightarrow S_i$) and their centroid C_i; and μ_i is the mean distance between all road segments in a cluster and its centroid.

TABLE 3. VARIABLE NAMES FOR ROAD CLUSTERING.

Variable [unit]	Description
$\boldsymbol{c_i}, \boldsymbol{i} = \{\mathbf{1..K}\}$	Index and set of road clusters for each center
$\boldsymbol{C_i}[\boldsymbol{X}, \boldsymbol{Y}], \boldsymbol{i} = \{\mathbf{1..K}\}$	The centroid of a cluster $\boldsymbol{c_i}$ and its coordinates
$\boldsymbol{nr_{c_i}}$	Number of roads in a cluster $\boldsymbol{c_i}$
$\boldsymbol{r_{c_i}}[\boldsymbol{X}, \boldsymbol{Y}]$	The start geo-position of a road in a cluster $\boldsymbol{c_i}$
$\boldsymbol{x_j} \boldsymbol{j} = \{\mathbf{1..}\boldsymbol{nr_{c_j}}\}$	Distance between a single road segment in a cluster $\boldsymbol{c_i}$ a nd the centroid of that cluster $\mathrm{C_i}$
$\boldsymbol{S_i}$ (I = {1.. K})	The collection of all road segments in a cluster
$\boldsymbol{\mu_i}$	Mean distance between all road segments in a cluster and its centroid
$\boldsymbol{d_m^{TC_i}}$[km]	Optimal road distance to be mowed based on the number of machines operating in each $\boldsymbol{TC_i}$
$\boldsymbol{N_{it}}$	the number of k-means iterations

The pseudo-code of the clustering algorithm is provided below:

Alg. 1. K-means clustering for road segmentation

Input: *N*, $\boldsymbol{TC_{i=\{1..N\}}}$ *[X,Y]*, $r_{c_i}[X,Y]$, N_{it}

Output: $C_i[X,Y], S_i$.

Init: $K = K_0$ *//choose the initial number of clusters;*

$S_i \leftarrow$ ***f_filter_road_segment_per_cluster(***$\boldsymbol{NR_{Z_i}^i}, \boldsymbol{TC_i}$ ***[X,Y])****//obtain the road segments assigned to initial clusters*

$C_i[X,Y] \leftarrow$ ***f_rnd_pos***$(\boldsymbol{c_i})$ *//place the centroids of each cluster randomly*

While $it \leq N_{it}$

for each road segment $r_{c_i} = 1 \ldots nr_{c_i}$

$C_i^0[X,Y] \leftarrow$ ***f_min***$(r_{c_i}[X,Y], C_i[X,Y])$

//find the nearest centroid

$\boldsymbol{S_i} \leftarrow$ ***f_append***$(\boldsymbol{r_{c_i}}[X,Y], C_i^0[X,Y])$

//assign the road segment to nearest cluster ***and append*** $nr_{c_i}++$

for each cluster j = 1..K

$C_i[X,Y] \leftarrow f\_mean(\mu_i)$ *// new centroid is placed at the mean of all distances between the assigned road segments and the cluster centroid.*

End

Overall, this clustering allows us to identify the centroids of each grouping of zones that need to be serviced in order to plan and optimize the minimal route, later defined in this section. Our review of the literature shows that this technique has not yet been applied to roadside mowing for planning purposes which makes it a unique approach for roadside mowing optimization. However, this technique has been used to address problems related to the concentration of pollutants [28] in the road space or on the deployment of roadside units to serve road traffic [29].

D. Finding the minimal path between all clusters

Once the clusters have been identified and selected, we propose to find the optimal path that would service among all the clusters by using the shortest routing API from TomTom [30]—which will be demonstrated in the Results section of the paper, while in the following we formulate the mathematical dependencies of this shortest path which is influenced by the number of available machines allocated to mowe the clusters and the optimal distance between the clusters based on the shortest path algorithm:

$$\boldsymbol{d_m^{TC_i}} = f_{TomTom}(m, nr_{c_i}, S_i) \qquad (2)$$

E. Multi-objective optimisation, assumption and constraints

In order to be able to express the objective functions, we need to determine the related variables with regards to costing and timing of each technical center, based on the area in each allocated cluster determined from Alg. 1, and the optimal distance calculated from Eq. 2. Given the staff/material costing provided by the industrial operator ($\boldsymbol{C_s^{TC_i}}, \boldsymbol{C_M^{TC_i}}$) we further estimate the staff cost per km, each technical center (summarized as well in TABLE 4):

$$\boldsymbol{C_{s\_km}^{TC_i}}[€/km] = \boldsymbol{C_s^{TC_i}}/\boldsymbol{d_m^{TC_i}} \quad (3)$$

$$\boldsymbol{C_{M\_km}^{TC_i}}[€/km] = \boldsymbol{C_M^{TC_i}}/\boldsymbol{d_m^{TC_i}} \quad (4)$$

Which can be used to calculate the total cost per center per number of kilometers:

$$\boldsymbol{CT_{km}^{TC_i}}\ [€/km] = \boldsymbol{C_{s\_km}^{TC_i}} + \boldsymbol{C_{M\_km}^{TC_i}} \quad (5)$$

Furthermore, we can obtain the marginal staff and material costs per machine, which are further used in the Scenario exploration from Section IV.

$$\boldsymbol{C_{s\_km\_m}^{TC_i}}[€/km] = \boldsymbol{C_{s\_km}^{TC_i}}/m \quad (6)$$

$$\boldsymbol{C_{M\_km\_m}^{TC_i}}[€/km] = \boldsymbol{C_{M\_km}^{TC_i}}/m \quad (7)$$

$$\boldsymbol{CT_{km\_m}^{TC_i}}\ [€/km] = \boldsymbol{C_{s\_km\_m}^{TC_i}} + \boldsymbol{C_{M\_km}^{TC_i}} \quad (8)$$

Similarly, we use the time utilization from previous mowing sessions ($\boldsymbol{ut_m^{TC_i}}$), and calculate the mowing time per km and the marginal mowing time per km per number of machines before identifying the total optimal time as follows:

$$ut_{m\_km}^{TC_i}[days/km] = ut_m^{TC_i}[days]/\, d_m^{TC_i} \quad (9)$$

$$ut_{m\_km\_m}^{TC_i}[days/km] = ut_{m\_km}^{TC_i}/m \quad (10)$$

$$ut_{m\_o}^{TC_i}[days] = d_m^{TC_i} * ut_{m\_km\_m}^{TC_i} \quad (11)$$

TABLE 4. VARIABLES FOR MULTI-OBJECTIVE OPTIMIZATION.

Variable [unit]	Description
$C_s^{TC_i}$[€]	Historical staff costs per TC_i
$C_{s\_km}^{TC_i}$[€]	Staff costs per km for each TC_i
$C_{s\_km\_m}^{TC_i}$	Staff costs per km and per machine in TC_i
$C_M^{TC_i}$[€]	Material costs for each TC_i
$C_{M\_km}^{TC_i}$[€]	Material costs per km for each TC_i
$C_{M\_km\_m}^{TC_i}$	Material costs per km and per machine for each TC_i
$CT_{km}^{TC_i}$[€]	Total cost per km for each TC_i
$CT_{km\_m}^{TC_i}$	Total cost per km and per machine in TC_i
$ut_m^{TC_i}$[days]	Total use time for machines in TC_i
$ut_{m\_km}^{TC_i}$[days/**KM**]	Total use time per km in TC_i
$ut_{m\_km\_m}^{TC_i}$[days/**KM**]	Total use time per km, pe machines in *each* TC_i
$ut_{m\_o}^{TC_i}$[days/]	Total optimal use time for *each* TC_i

Once all parameters are identified, we formulate the multi-objective criteria that we would like to meet for each TC_i:

$$\begin{cases} F_1^{TC_i} = \min\limits_{m=1.M_{TC_i}} \left\{ d_m^{TC_i} \cdot CT_{km}^{TC_i} \right\} \\ F_2^{TC_i} = \min\limits_{m=1.M_{TC_i}} \left\{ ut_{m\_o}^{TC_i} \right\} \end{cases} \quad (12)$$

So that

$$\begin{cases} a)\ 0 \le d_m^{TC_i} \le 2 \cdot \sum_{nr_{c_i}} Length(r_{c_i}) \\ b)\ 0 \le m \le MTCi \\ c)\ \{S_1, \dots S_i\} \in TC_i \end{cases} \quad (13)$$

Where $F_1^{TC_i}$ represents the minimization of the total costs spent by each TC_i on staff and material in order to deliver the optimal route for servicing the routes in each allocated cluster while $F_2^{TC_i}$ represents the minimization of the total use time of the centers, based on the optimal distance identified from the clustering and the number of available machines to mowe.

In order to meet these criteria, we make the following assumptions and conditions:

1. The optimal distance that the machines need to operate is non-null and can reach a maximum of double the length of all roads for a center (as the roads need to be mowed on each side of the road—see Eq. 13 a)
2. The number of machines in use can't overpass the capacity of a center and are limited in number (see Eq. 13b).
3. All roads allocated to individual clusters in an area must fall under the operation of a single center (see Eq. 13c).
4. The machines are similar in performance and costs; while different centers might employ different tools, for simplifying the analysis, we assume uniformity in performance.
5. The formulas are provided for a single mowing season, and where multiple mowing seasons per year will be undertaken by each center, the results need to be recalculated every time for each mowing season.
6. We treat all roads the same, but in the future, the same analysis can be fragmented for different types of roads (primary, secondary, tertiary with additional constraints).
7. A centroid of a cluster represents the center of a specific sub-territory that need mowing. The machines reach first the center for this sub-territory and then they mow all routes allocated to that particular sub-territory before mowing along the shortest route to the next sub-territory center.

IV. RESULTS

The Vosges area is serviced by 16 technical centers and is comprised of 75098 road segments, among which of which 2507 are classified as primary, 3494 as secondary and 3591 as tertiary. In order to showcase the methodology and the results, we focus on this paper on the exemplification and optimization for the Neufchteau technical center (north-west of the Vosges department), while the rest of the centers follow the same procedure. This center is at the north-west of the network to be maintained, and it is not impacted by the presence of valleys and mountains, which strongly constrain the mowing routes.

After applying the road segmentation, 8 clusters have been identified for the Neufchateau area, and their centroids are shown in Fig 4 with their relevant road segments associated with them.

Fig 4. Segmentation of the canton of Neufchâteau using K-Means Clustering.

In order to analyze the impact of the number of machines and their availability would have on the overall costs and use times, we create 5 different scenarios and showcase the analysis and results for each of them, followed by the overall optimization analysis at the end of this section.

A. Scenario 1: using one single mowing machine

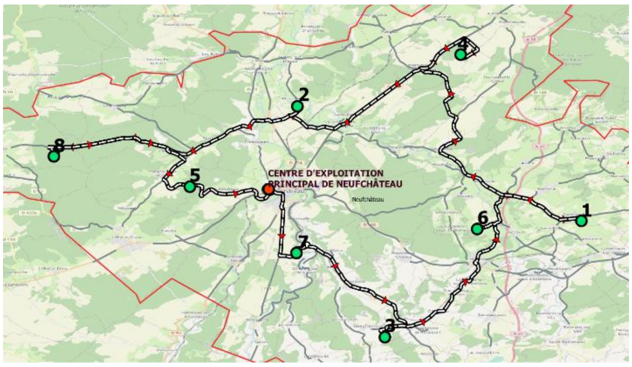

Fig 5. Scenario 1 optimal routing among all cluster centroids using a single mowing machine.

For simplifying the visual representation and understanding of the concept, we only plot the minimal and optimal routing that a single machine needs to do among the clusters (see Fig 5). However, we could plot all the routes back and forth in all directions, but this would be hard to interpret and analyze. We also analyze two mowing seasons per year—one in spring (less costly and lengthy) and one in summer, which requires more operations due to the higher amount of vegetation. The results are therefore reported for each mowing season as well as per year.

The ideal minimal routing, in this case, would be: $\boldsymbol{TC_i} \rightarrow 7 \rightarrow 3 \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 2 \rightarrow 8 \rightarrow 5 \rightarrow \boldsymbol{TC_i}$. Covering a total of 322.6km, which would take 38 days for the first mowing season and 77.78 days for the second season. However, having access to only one machine would mean restricted resources and constrained planning and increased times to deliver all routes in all directions.

B. Scenario 2: using two mowing machines

Fig 6 showcases the optimal routing when using two mowing machines that need to service the following sequence of clusters:

$$\boldsymbol{m=1}: \boldsymbol{TC_i} \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 2 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m=2}: \boldsymbol{TC_i} \rightarrow 7 \rightarrow 3 \rightarrow 5 \rightarrow 8 \rightarrow \boldsymbol{TC_i}$$

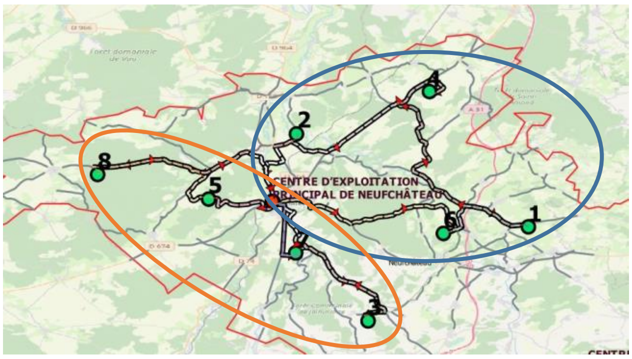

Fig 6. Scenario 2—optimal routing using two machines.

The machines are better optimizing the travel distance between clusters and manage to reduce the travel time for the two mowing seasons by 40% with, however, an increase in cost due to additional staff members for operating the vehicles and purchase/maintenance costs adding to the regular costs.

C. Scenario 3: using three mowing machines

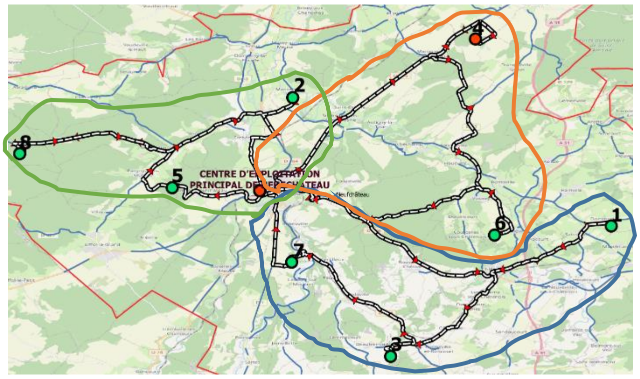

Fig 7. Scenario 3—optimal routing using three machines.

Fig 7. showcases the optimal routing when using three mowing machines which need to service the following sequence of clusters:

$$\boldsymbol{m=1}: \boldsymbol{TC_i} \rightarrow 1 \rightarrow 3 \rightarrow 7 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m=2}: \boldsymbol{TC_i} \rightarrow 4 \rightarrow 6 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m=3}: \boldsymbol{TC_i} \rightarrow 5 \rightarrow 8 \rightarrow 2 \rightarrow \boldsymbol{TC_i}$$

This case represents a more fine-grained coverage of the mowing area; however, the annual costs almost triple in this scenario due to extensive manpower and purchase/maintenance costs of the machines, making it less attractive than the previous scenario.

D. Scenarios 4 and 5: using four and 5 mowing machines

Scenarios 4 and 5 represent similar clustering optimization, which we represent via the same Fig 8, due to repetitive routing that appears when adding more machines to the operations. The optimal cluster routing paths are provided below:

Scenario 4 presents very short paths from the center to each cluster, with only two major areas (clusters) services by each machine before returning to the station.

$$\boldsymbol{m=1}: \boldsymbol{TC_i} \rightarrow 3 \rightarrow 7 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m=2}: \boldsymbol{TC_i} \rightarrow 6 \rightarrow 1 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m=3}: \boldsymbol{TC_i} \rightarrow 4 \rightarrow 2 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m=4}: \boldsymbol{TC_i} \rightarrow 5 \rightarrow 8 \rightarrow \boldsymbol{TC_i}$$

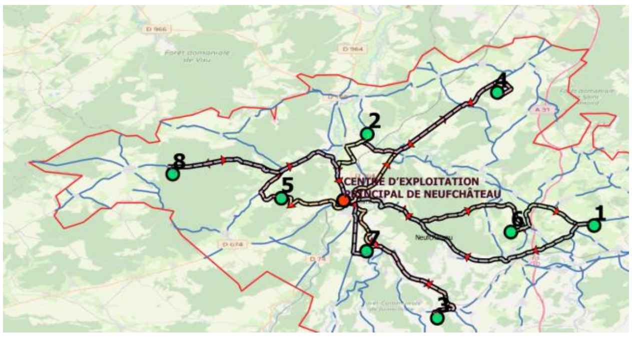

Fig 8. Scenario 4—optimal routing using four/five machines.

Similarly, Scenario 5 presents the same 3 routes as Scenario 4, and in addition, two even shorter paths with only one cluster to be serviced by a single mowing machine; this aspect makes the costs increase significantly in terms of staff and material maintenance (almost twice from Scenario 2) but with limited benefits due to an overall shorter operational time for each machine:

$$\boldsymbol{m} = \mathbf{1}: \boldsymbol{TC_i} \rightarrow 3 \rightarrow 7 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m} = \mathbf{2}: \boldsymbol{TC_i} \rightarrow 1 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m} = \mathbf{3}: \boldsymbol{TC_i} \rightarrow 4 \rightarrow 2 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m} = \mathbf{4}: \boldsymbol{TC_i} \rightarrow 6 \rightarrow \boldsymbol{TC_i}$$

$$\boldsymbol{m} = \mathbf{5}: \boldsymbol{TC_i} \rightarrow 5 \rightarrow 8 \rightarrow \boldsymbol{TC_i}$$

We finally centralize all results in Fig 9 and provide a 3D representation across all scenarios for the total cost, use time, optimal distance based on the number of machines and the mowing seasons per year. The blue and red lines indicate the spring and summer mowing seasons, while the green line the added yearly costs in a single trending line. Each circle represents the number of mowing machines corresponding to each scenario, with the lowest ones being m=1, while the highest ones are representing results for m=5.

The findings reveal that Neufchateau reaches a minimal and optimal cost and time utilization for a number of two machines, above which the cost and time effort invested in the utilization of additional equipment becomes non-sustainable in the long term; this being the main reason why the number of machines tested for this center was limited to 5. Similar analysis can be undertaken for the rest of the centers, which have a similar setup.

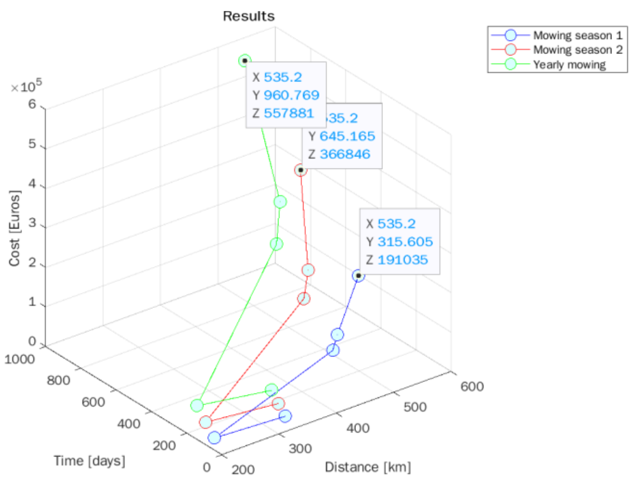

Fig 9. 3D representation across all scenarios for Cost, Time, Distance based on the number of machines and the mowing seasons per year.

V. CONCLUSIONS

In this paper, we present a pioneering approach for roadside mowing aimed to support planners work in the optimization of resources related to the specific features of a territory. The proposed approach is based on a road segmentation and clustering approach using k-means, followed by the shortest path routing application and multi-objective optimization for determining the best number of mowing machines that technical centers can use for delivering annual road maintenance.

Limitations of this study: a) as previously mentioned, our study considers all road types to be mown similarly, which might not be the case for real-life applications and prioritizations; b) we consider the mowing machines to be of the same type, but in reality, each center might have various tractors/tools to operate, with various costs and use times, c) we have presented the optimal pathway for delivering clustering of roads, and help the center prioritize operations, but for real-life applications, more sequential operations could arrive based on staff availability, weather, etc. d) other clustering methods could have been applied, but due to the main focus on the paper, we relied more on the optimization approach and problem formulation.

Future work: a) two important aspects to consider in the road mowing optimization are the emissions being generated by different machines, as well as the waste collection during the mowing operations. We are currently looking at extending the current study for reducing waste and CO_2 emissions with the help of the industry partner; b) the current approach can be used for local optimization while a global approach might be needed for larger areas that rely on a sharing of resources among centres'; this hypothesis will imply additional constraints in the multi-objective optimization function, together with more extended use-case scenarios.

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