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Notes Notes

Abstract

Adequate public charging infrastructure for battery electric trucks (BETs) is crucial for electrifying road freight transport and, thus, curtailing greenhouse gas emissions. Although manufacturer announcements on BET sales targets are promising, many logistic companies still question their technical feasibility due to the limited all-electric range and insufficient public charging infrastructure. Therefore, knowing the attractiveness of truck stop locations and their relevance for ensuring operational schedules is essential to facilitate the coordinated deployment of public charging infrastructure while its profitability is almost pre-secured.

This paper aims to characterize current truck stop locations and evaluate possible public charging station locations for BETs via multi-criteria analyses using Geographical Information Systems (GIS) data. This study benefits from real-world truck stop location data, including geo-coordinates and occupancy data, and uses several GIS data sources to enhance the data and verify the presence of distinct truck-relevant features. Features may comprise the proximity to the TEN-T highway network or infrastructure availability, such as fueling stations or rest areas. Additionally, correlation and archetypal analysis are applied to better understand truck stops and their feature dependencies.

The results demonstrate the high attractiveness of industrial areas with many potential business destinations along the TEN-T network. However, no particular feature determines the attractiveness of truck stop locations, but the distinct feature combination is decisive. The archetypal analysis reveals three extremes that may constitute the backbone of a public German charging infrastructure network: (1) industry hotspots, (2) hosted rest areas or truck stops along the TEN-T network, (3) and public truck parking areas with additional services.

Finally, 1,648 public parking and rest areas in Germany are identified using OpenStreetMaps.org (OSM) data, and their attractiveness for future BET charging infrastructure is evaluated. These results are provided in an interactive HTML-based map.

Contents

1 Introduction

Limiting global warming to well below 1.5 degrees forces all countries to rapidly reduce their greenhouse gas (GHG) emissions across all sectors. While the European Union is committed to climate neutrality by 2050, the transport sector currently emits about one-quarter of the EU's energy-related GHG emissions. While heavy-duty vehicles account for under one-tenth of total vehicle stock, their contribution is around 20% of all transport-related emissions (European Commission 2020).

Battery-electric trucks (BETs) are one promising option to reduce those emissions. Certain models are already available or have been announced by all European truck manufacturers for the next years. Fortunately, BETs benefit from recent passenger car battery innovations such as rapidly decreasing production costs, increasing volumetric energy density and specific energy, enhanced cyclic and calendrical aging, and improved fast charging capability (Phadke et al. 2021; Nykvist and Olsson 2021). However, one crucial factor for the widespread adoption of BETs is an adequately developed charging infrastructure to facilitate convenient and reliable operations (Metais et al. 2022). This raises the first central research question: Where to build charging infrastructure for BETs?

EU policymakers have addressed this issue, yet concrete recommendations and site locations are uncertain. The recently presented "Fit for 55" package by the European Commission proposes an Alternative Fuels Infrastructure Regulation (AFIR) so that a minimum of charging locations for trucks along the most important European highways (TEN-T network) will be mandatory (European Commission 2021). However, the concrete realization will be handed to the national authorities. Exemplary, the National Centre for Charging Infrastructure (NLL) in Germany hosts the so-called "StandortTool" (National Centre for Charging Infrastructure). This tool is based on transport demand modeling using geospatial and socio-economic data, vehicle owner mobility patterns, and grid infrastructure to extrapolate the number of charging events per area and highlight particularly well-suited areas. However, this tool only handles passenger cars and may be updated to handle trucks since those are subject to distinct operations schedules with pre-defined driving or stopping times and have higher space requirements. This raises a second upstream research question: How to characterize current truck stop locations?

While charging infrastructure site selection is well documented and differentiated for passenger cars, insights for heavy-duty trucks are few. Here, Metais et al. (2022) provide a quite recent overview. Moreover, the better availability of empirical data from passenger car charging infrastructure facilitates a higher level of detail, particularly using Geographical Information Systems (GIS) data. Mortimer et al. (2022) proposed an installation procedure based on real-world utilization data from over 21,000 charging stations, matched those data to 23 categories with places of common interest (POI), calculated the correlation using linear regression, and used these findings to extrapolate expansion strategies on so far unexploited areas. Schmidt et al. (2021) proposed a five-stage multi-criteria and GIS-based location methodology using a light beam search heuristic to constitute different service networks in Poznan, Poland. Kaya et al. (2020) used a multi-criteria decision analysis (MCDA) with differing weighting methods and covering socio-economic, geographical, energy-supply, traffic and road network, and POI data for the optimal planning of new sites in Istanbul, Turkey.

In summary, while well-known frameworks and multiple assessments for passenger cars exist, detailed insights for truck charging infrastructure are limited. Consequently, this paper aims to characterize current truck stop locations, determine enhancing factors on the attractiveness of such locations, and determine the potential attractiveness of parking and rest areas for future BET charging infrastructure. Findings may support a coordinated charging infrastructure deployment for trucks and help infrastructure providers find the most attractive locations.

This paper is structured as follows. Section 2.1 describes the data, covering the published GPS truck stop data (Plötz and Speth 2021) and the data enhancement process using different sources. Section 2.2 introduces the GIS-based multi-criteria decision analysis and the archetypal analysis. Section 3 contains the results, covering characteristics of current truck stop locations and the attractiveness of potential parking and rest areas for future BET charging infrastructure. This paper closes with a discussion in Section 4 and conclusions in Section 5.

2 Data and Methods

2.1 Data

2.1.1 Truck Stop Data

This paper uses European truck stop data from the European Association of Automobile Manufacturers (ACEA), including seven truck manufacturers (OEM) and heavy diesel trucks with over 7.5 tons of gross vehicle weight. Explicitly, data originate from Plötz and Speth (2021), who processed these coordinates as part of the "Truck Stop Locations in Europe" study. This published data includes the geographic coordinates and occupancy data (number of daily stops - nos).

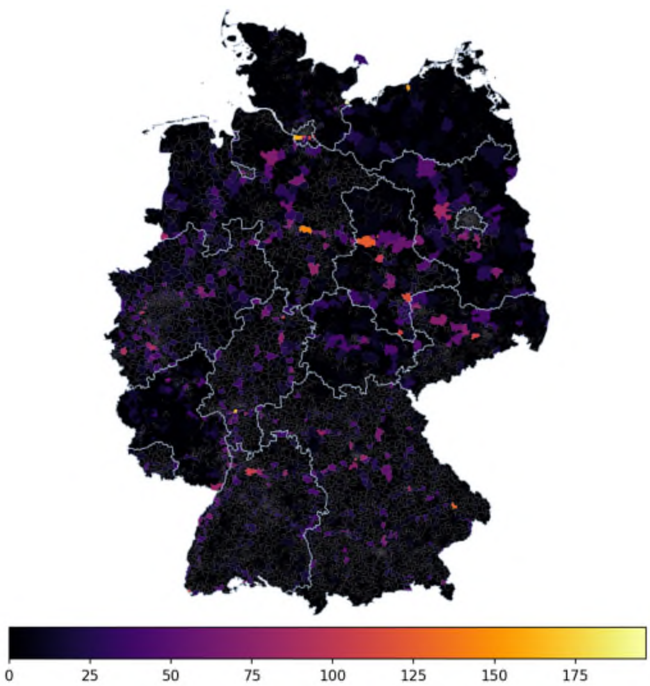
Geographic coordinates

From over 750,000 GPS-based locations recorded over one year, using several filter criteria and the DBSCAN algorithm yielded 31,145 clustered locations covering long-haul trucks stopping for at least 30 minutes. Clusters contain at least three original locations with data from at least three OEMs. Usual cluster sizes range from 300 to 450 meters. Note that geographic coordinates represent the cluster centroids.

While data coverage for certain small European countries is limited, coverage for Central, Western, and Northern Europe is more representative (Plötz and Speth 2021). The German dataset covers $m = 7{,}456$ locations. Figure 1 visualizes the number of daily stops in Germany accumulated per postal code area:

Figure 1: Average number of daily stops in Germany per postal code area

Dark postal code areas are those with few stops per day, while light postal code areas are those with many stops per day.



Source: Own calculations based on ACEA data (see Plötz and Speth 2021).

The number of daily stops per location differs significantly (cf. Table 1), and most locations exhibit only low to medium numbers of daily stops (Plötz and Speth 2021). Owing to this skewness, the 50 percent least frequented stop locations have only 1.6 daily stops on average. In contrast, the top 10 percent locations are responsible for over 50 percent of all daily stops and contribute around 24 daily stops on average. Overall, the $m = 7{,}456$ truck stop locations entail 34,452 daily stops, resulting in 4.6 daily stops on average.

Table 1: Summary statistics of truck stop location data

Empirical study of truck stop locations in Germany.

Average number of daily stops	4.6
Median number of daily stops	1.6
Standard deviation number of daily stops	8.6
Maximum number of daily stops	191
Sum of daily stops over all locations	34,452
Share of locations with > 10 stops per day	12%
Average number of daily stops of top 10% locations	24.5
Share of daily stops generated by top 10% locations	53%

Source: Own calculations based on ACEA data (compare Plötz and Speth 2021).

2.1.2 Feature Data

The data enhancement process assigns corresponding features to each stop location to understand local conditions that may affect the attractiveness. Feature selection is inspired by expert opinions and findings from similar studies, such as Kaya et al. (2020), Mahmud et al. (2020), Mortimer et al. (2022), Plötz and Speth (2021), Schmidt et al. (2021) and Yagmahan and Yılmaz (2022). This selection comprises socio-economic, geographical, traffic, TEN-T road network, electricity grid, and POI data. We use different sources to enhance accuracy. We categorize all features into five categories with the following features (cf. Table 2):

Table 2: Potential features for truck stop location characterization

Potential characteristics of truck stop locations that may affect the attractiveness of locations. Total of $n = 24$ features for current truck stop locations and $n^* = 26$ features for future charging infrastructure locations for BETs. All features as point-related variables, except Land Use.

- **Road Network ($j = 1, 2$)**
  - TT1: TEN-T Core Network
  - TT2: TEN-T Comprehensive Network
- **Industry & Cargo ($j = 3, \dots, 9$)**
  - HA: Harbour
  - BH: Train Station
  - FH: Airport
  - GU: Other hubs for handling of goods
  - GI: Commercial / Industrial Zone
  - ME: Exhibition Area
  - GM: Wholesale Market
- **POIs ($j = 10, \dots, 19$)**
  - PP: Parking Area
  - WC: Toilet Facilities
  - RA: Rest Area
  - RE: Restaurant
  - TA: Gas Station
  - AH: Autohof *
  - HO: Hotel / Motel
  - SH: Shop
  - WA: Car Wash
  - WS: Garage
- **Land Use ($j = 20, \dots, 24$)**
  - Urb: Urban Area
  - InCom: Industrial / Commercial Area
  - Tra: Transport Area
  - Art: Other Artificial Area
  - Oth: Other or Unknown (e.g. green area)

BETs only:

- **Grid Connection ($j = 25, 26$)**
  - EV: EV Charging Station (for passenger cars)
  - UW: Substation

* Gas station with restaurants and parking area aside the highway

Source: Own compilation based on literature review and expert opinions.

The category *Road Network* involves the proximity of locations to the TEN-T network, whereas we differentiate between the Core and the Comprehensive Network as defined by the European Commission DG MOVE - TENtec Information System. The nearest distance of any location to the networks is calculated as an aerial distance (haversine formula) and, thus, unambiguous.

The category *Land Use* incorporates information on the biophysical characteristics of the Earth's surface based on CORINE Land Cover (CLC) data provided by the Copernicus Land Monitoring Service (CLMS) (Copernicus Programme 2022). The affiliation of any location to a CLC class is unambiguous. We use 2018 as the latest available reference year.

The categories *POI* and *Industry & Cargo* incorporate information on specific conditions at the respective location, thus characterizing the location more precisely. This information is based on different data sources such as HERE (2022), TomTom International B.V. (2022), the National Organisation Hydrogen and Fuel Cell Technology (NOW) in Germany, AUMA (Ausstellungs- und Messe-Ausschuss der Deutschen Wirtschaft e.V. 2021) and GFI (Gemeinschaft zur Förderung der Interessen der Deutschen Großmärkte e.V. (GFI) 2009). One location may have several POI labels.

Further attributes are required to reflect particularities for charging infrastructure. Thus, we include an additional category *Grid Connection*, covering two aspects: (1) The availability of surrounding grid substations to represent a potential cost-minimal expansion; (2) The availability of existing charging infrastructure for passenger cars to represent a potential utilization of synergies.

2.1.3 Parking and rest areas for future BET charging infrastructure

Potential parking and rest areas are identified using OSM data (via overpass-api.de) and validated with highway rest area data from the NOW GmbH and TomTom Geocoding API. This approach is chosen since OSM does not guarantee data completeness or correctness but offers simple, fast, and free queries for whole countries. In contrast, TomTom delivers more reliable results and specializes in truck sector operations but misses the possibility of retrieving all country-specific truck parking locations. Therefore, we use TomTom to filter the OSM data. Similarly, we validate our data with locations of rest and parking areas along the highway provided by the NOW GmbH.

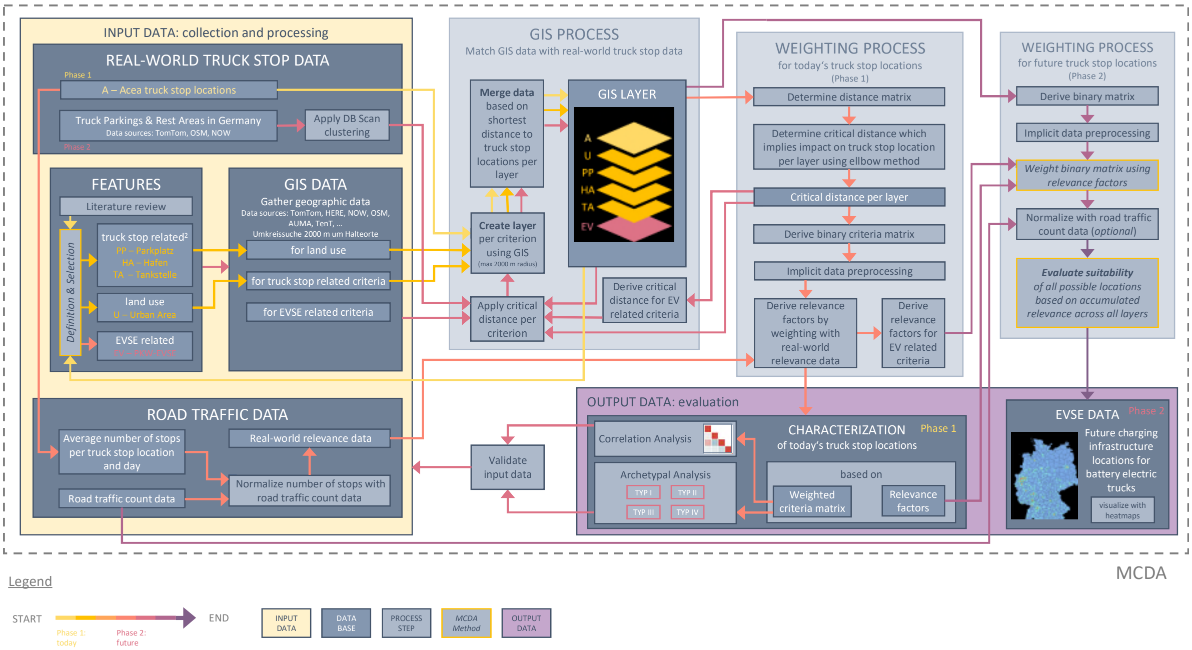
This leads to $p = 1{,}648$ public, truck-accessible, and non-private parking areas in Germany. Semi-public and private truck parking areas, such as on company premises, are not included in this data and, thus, not evaluated. Note that we clustered nearby locations to overcome not exactly matching geo-coordinates for the same location or to combine charging locations on opposite street sides.

2.2 Methods

Our multi-criteria and GIS-based assessment involves two phases and follows, in general, the process from Kaya et al. (2020). Moreover, we perform several statistical analyses, such as clustering and archetypal analysis, to improve the understanding of feature dependencies. Figure 2 visualizes the process. All process steps are explained below, and all calculations are executed with Python.

Figure 2: Multi-criteria and GIS-based evaluation method

GIS-based multi-criteria decision analysis (MCDA). Phase 1: Determination of feature weights for current truck stop locations. Phase 2: Evaluate the attractivenss of potential parking and rest areas for future charging infrastructure locations for BETs.



Source: Own visualization based on Kaya et al. (2020) and Wang et al. (2009).

2.2.1 GIS-based MCDA

Phase 1: Characterization of today's truck stop locations

First, the distance matrix $D^{m \times b}$ contains the minimal aerial distance (haversine distance) in meters between truck stop locations and each point-related feature, with a cut-off search radius of 2000 meter. The features of the category *Land Use* are an exception since its an area-related feature so that one of the five *Land Use* features may be assigned unambiguously. This results in a distance matrix D of dimension $m \times b$ with m truck stop locations and $b = n - 5 = 19$ as the total number of features without the feature group *Land Use*:

$$D = \begin{pmatrix} d_{11} & \cdots & d_{1b} \\ \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mb} \end{pmatrix} \quad (1)$$

Second, using the elbow method yields the maximum relevant distance per feature and thus prevents data noise(see Appendix A.1). For each feature, all occuring distances are collected and the resulting distance vector is sorted in ascending order. Given all these occurring distances, we derive the empirical cumulative density function (ECDF) $f_{ECDF,j}$ and apply the elbow method heuristic for each feature j. This method determines where the ECDF has its maximum curvature, representing the distance from which the incremental benefit per additional relevant distance decreases. To reflect uncertainty regarding cluster size and centroid (cf. Section 2.1), we set the minimum value to 500 meter. Thus, the final critical distance FCD_j for each feature is calculated as follows:

$$FCD_j = \max\{CD_j; 500\}, \qquad j = 1,2,\dots,b = TT1, TT2, HA, \dots, WS \tag{2}$$

Our results show that values range from 500 to 830 meters for the final critical distance (see Table 5 in Appendix A.1).

Third, we derive the binary feature matrix $X^{m\times n}$, which shows whether there is a feature j within the respective FCD_j for each truck stop location i:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{3}$$

For all $j = 1,2,\dots,b$, we define x_{ij} as

$$x_{ij} = \begin{cases} 1, & if\ d_{ij} < FCD_j\,, \\ 0, & else\,, \end{cases} \qquad i = 1,2,\dots,m\,, \tag{4}$$

and for features $j = n-4, n-3, \dots, n$, we add the information about the respective *Land Use* depending on if the feature is assigned ($x_{ij} = 1$) or not ($x_{ij} = 0$).

Fourth, we integrate the average number of daily stops nos for each truck stop location to determine feature importance. This contradicts typical subjective MCDA methods such as AHP, PROMETHEE, or VIKOR to determine such weightings. Based on the binary feature matrix X, we can finally specify the weight w_j of each feature j using the average number of stops per day nos_i of each truck stop location i. These are calculated as follows:

$$w_j = \frac{\sum_{i=1}^{m} x_{ij} nos_i}{\sum_{j=1}^{n}\sum_{i=1}^{m} x_{ij} nos_i}, \qquad j = 1,2,\dots,n \tag{5}$$

These weights quantify the importance of parking characteristics for truck stop locations and sum up to 100 percent. By sorting those feature weights in descending order, we can assign a rank to each feature and determine the most important ones.

Afterward, we will use both the binary matrix and the feature weights as interim results for subsequent statistical analyses (see Section 2.2.2).

Phase 2: Attractiveness evaluation of public parking areas for future charging locations for BETs

As empirical weighting was impossible for the category *Grid Connection*, we assume suitable weights by setting the median value from w_j and subsequently normalize all feature weights, which yields normalized feature weights $w^*{}_j$.

Fifth, we apply those feature weights on the $p = 1{,}648$ potential charging infrastructure locations for BETs in Germany and set up the binary feature matrix X^* (cf. matrix X).

Sixth, according to the evaluation process of MCDA (compare Wang et al. 2009), we chose the weighted sum method (WSM) for determining a score for each location. This results in the following adjusted formula for calculating the score S_{i^*} of a parking location i^*:

$$S_{i^*} = \sum_{j=1}^{n^*} w^*{}_j x_{i^*j}\,, \qquad i^* = 1,2,\dots,p \tag{6}$$

mit

$$w^*{}_j = \frac{w_j}{\sum_{j=1}^{n^*} w_j}, \qquad j = 1,2,\dots,n^* \tag{7}$$

The score S_{i^*} can be interpreted as the attractiveness of the truck parking location for charging infrastructure for BETs with best decision alternative corresponding to the parking location with the maximum score (compare Wang et al. 2009).

Visualization

Finally, we visualize our findings in two ways: (1) Potential parking and rest areas are published via an interactive HTML-based map using the python package "folium" according to Plötz and Speth (2021). The locations are mapped as circles with a radius of 500 meter around their geographic coordinates (cluster centroid) and the attractiveness score S_{i^*} is color-coded, similar to the heat maps by Mortimer et al. (2022) and Kaya et al. (2020). (2) An aggregated heat map highlights postal code areas with many locations, particularly suitable locations, or both. For this purpose, we cumulate the scores of the truck parking locations per postal code area, normalize the results, and visualize the color-coded postal code areas.

2.2.2 Statistical Analyses: Correlation Analysis, Archetypal Analysis & Clustering

Correlation Analysis

Based on the binary matrix in Phase 1, we can now investigate the relationship between features by running a correlation analysis. For this purpose, the binary feature matrix is weighted with the average number of daily stops nos for each of the m truck stop location as follows:

$$X_{weighted} = X * \overrightarrow{nos}, \qquad \overrightarrow{nos} = (nos_1, nos_2, \dots, nos_m) \tag{8}$$

We use Spearman's rank correlation and apply this to the weighted matrix $X_{weighted}$ using the python package „scipy.stats.spearmanr" (Virtanen et al. 2020). Additionally, we prove the significance of the correlation coefficients determining the p-values.

Archetypal Analysis & Clustering

The archetypal analysis allows the identification of extreme observations (so-called archetypes) in high-dimensional data sets and, thus, captures heterogeneity among observations rather than homogenizing these observations, as done by common cluster analyses. These archetypes are selected by minimizing the squared error of each observation as a mixture of archetypes using the Python package (Alcacer 2021).

Using archetypal analysis, we identify three archetypes in the feature characteristics of truck stop locations. Each archetype represents a different combination of features at the stop locations, from which all real combinations can be reproduced.

The results of this analysis are shown in Figure 3, which represents the $k = 3$ archetype vectors $\vec{a_l}$ with the respective specification a_{lj} regarding all n features. An archetype vector $\vec{a_l}$ is composed as follows:

$$\vec{a_l} = (a_{l1}, a_{l2}, \dots, a_{ln}), \qquad l = 1, 2, 3 \tag{9}$$

However, further analysis is necessary to understand how many truck stops are represented by each archetype and, thus, which one could be most important.

For this purpose, we design an "affiliation" formula for calculating the similarity or affiliation of a truck stop location to the three different archetypes. We describe the affiliation z_{il} of a stop location i to an archetype vector $\vec{a_l}$ with the feature values a_{lj} as

$$z_{il} = \frac{\sum_{j=1}^{n} x_{ij} a_{lj}}{\sum_{j=1}^{n} a_{lj}}, \qquad i = 1,2, \dots, m, \qquad l = 1, 2, 3 \tag{10}$$

with x_{ij} representing the binary variable indicating the presence of feature j at truck stop location i (compare Section 2.2.1).

This affiliation z_{il} describes how strongly a truck stop location corresponds to an archetype. The values of z_{il} varies between 0 and 1. Using these affiliations, we can generate affiliation tuples $z_i = (z_{i1}, z_{i2}, z_{i3})$ to the three archetypes for all truck stop locations. Please note, that our affiliation formula does not penalize the presence of additional features, as those would only improve the attractiveness of a location and thus do not need to be considered negatively. Figure 4 visualizes the results of the affiliation calculations for all stop locations.

At this point, it would be possible to rank the affiliation values of a truck stop location to determine which archetype the location most closely corresponds to. The archetype l with $z_{il} = \max\{z_{i1}, z_{i2}, z_{i3}\}$ would be the closest to the truck stop location i. However, since we discover that the results show very similar values in the affiliation tuples, this one-dimensional interpretation should be avoided.

Therefore, we apply a DBSCAN clustering instead to recognize three-dimensional patterns in the affiliation tuples using „sklearn.cluster" in Python (Pedregosa et al. 2011). This yields six clusters.

3 Results

3.1 Characterization of today's truck stop locations

Based on the feature weights derived from the average number of stops per truck stop location, we evaluate the importance of the features for current truck stops. Table 3 shows the weights in percent, sorted by feature group. In addition, the rank of the feature is given. Our results show the strongest weights for the features GI (Commercial / Industrial Zone), PP (Parking), WC, RE (Restaurant), and WS (Garage).

Table 3: Feature weights and ranks of feature importance

Feature groups relevant for today's truck stop locations.

Feature Group	Feature	Name	Feature weight w_j	Rank
Road Infrastructure	TT1	TEN-T Core Network	5.28%	10
	TT2	TEN-T Comprehensive Network	1.83%	13
Industry & Cargo	HA	Harbour	0.31%	19
	BH	Train Station	0.77%	17
	FH	Airport	0.13%	20
	GU	Other hubs for handling of goods	5.24%	9
	GI	Commercial / Industrial Zone	12.07%	1
	ME	Exhibition Area	0.03%	23
	GM	Wholesale Market	0.08%	22
POI	PP	Parking Area	11.62%	2
	WC	Toilet Facilities	10.63%	3
	RA	Rest Area	4.14%	11
	RE	Restaurant	8.55%	4
	TA	Service Station	5.28%	10
	AH	Autohof	1.27%	14
	HO	Hotel / Motel	2.71%	12
	SH	Shop	5.90%	7
	WA	Car Wash	1.12%	15
	WS	Garage	8.02%	5
Land Use	Urb	Urban Area	0.71%	18
	InCom	Industrial / Commercial Area	7.54%	6
	Tra	Transport Area	0.89%	16
	Art	Other Artificial Area	0.12%	21
	Oth	Other or Unknown	5.66%	8

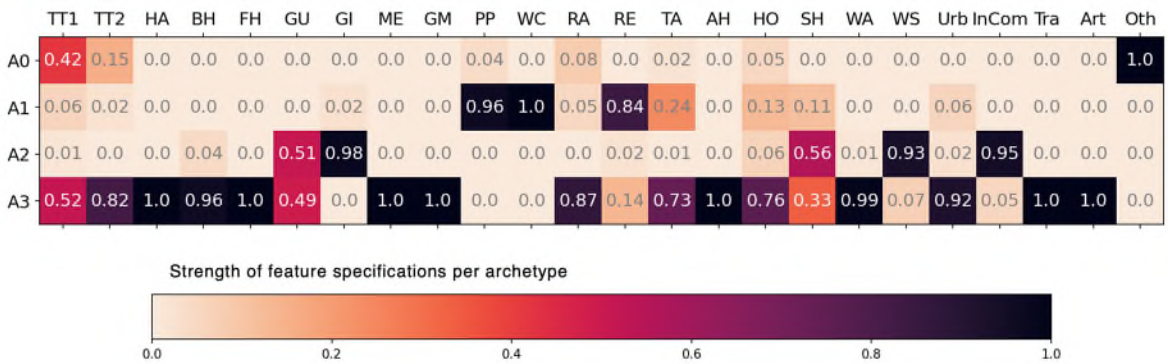
Source: Own calculations.

Spearman's rank correlation results show several moderate to strong correlations between features. We can derive positive dependencies between the feature group *Road Infrastructure* and *POI*, while features from *Industry & Cargo* negatively correlate with *Road Infrastructure*. Further results are shown in Figure 8 (see Figure 8, Appendix A.2).

Figure 3 shows the three archetype vectors and their particular feature relevance. The three archetypes comprise hosted rest areas along the Ten-T network (Archetype A0), public truck parking lots with additional services such as toilet facilities or restaurants (Archetype A1), and industrial areas with shops and garages (Archetype A2).

Figure 3: Archetype vectors with the respective feature specifications

Archetype vectors A0, A1 and A2 with the respective specification regarding all features. A3 is the residual vector, including all non-archetypal features.

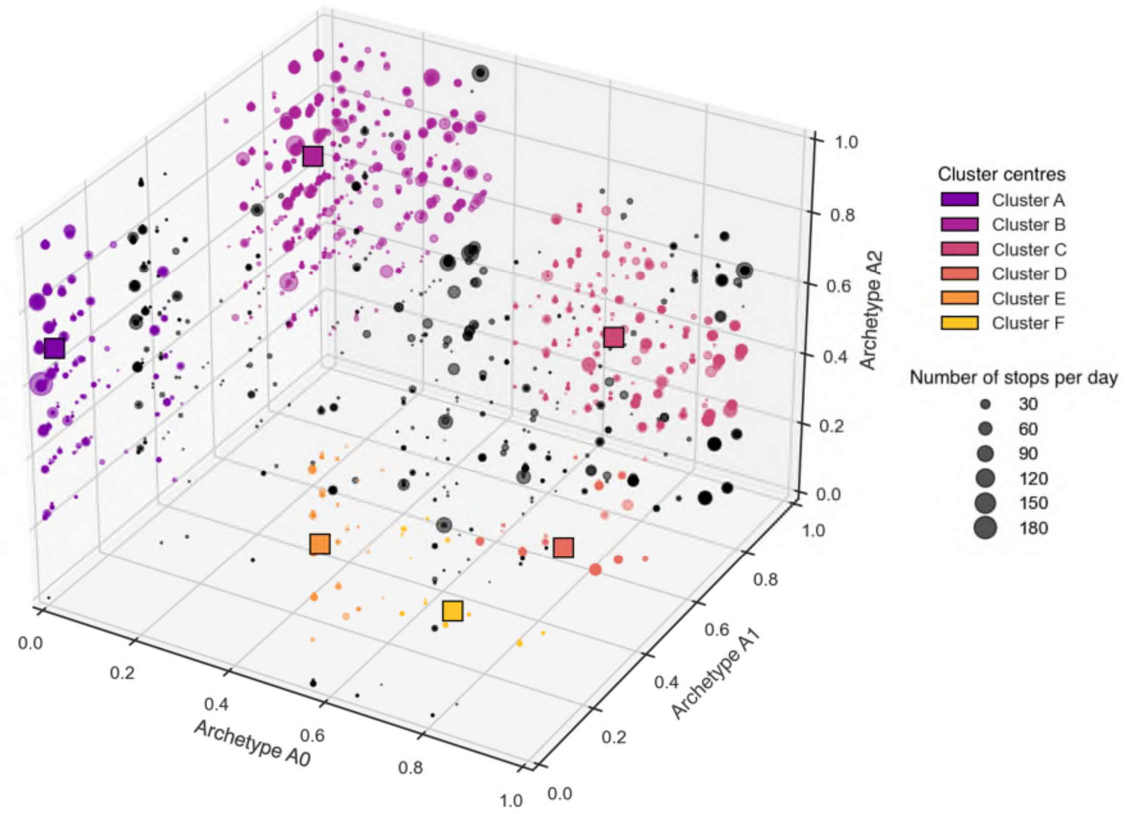


Source: Own calculations.

Figure 4 shows the results of our further affiliation analysis and clustering: the association of the $m = 7{,}456$ truck stop locations with the archetypes A0, A1, and A2. A circle represents a truck stop. The affiliation to the three archetypes is plotted on the three axes using the affiliation tuples $z_i = (z_{i1}, z_{i2}, z_{i3})$, that we calculated previously. The size of the circles represents the average number of stops per day at each stop location. Overlaps arise from identical affiliations to the three archetypes for multiple stopping places.

Figure 4: Archetypal analysis and clustering of affiliation tuples

Three-dimensional visualization of truck stop locations regarding their affiliation to the archetype vectors A0, A1, and A2 with associated clustering and indicating the respective average number of stops per day. Six clusters distinguishable with cluster centers as rectangles.



Source: Own calculations.

Table 4 shows the average affiliation values of the three archetypes for all six clusters and indicates the importance of the respective cluster by providing information about the number of stop locations corresponding to the cluster and the average number of daily stops at those locations. We identify three main clusters, visualized in Figure 4, with their cluster centers as rectangles:

With 69% affiliation, Cluster A belongs mostly to Archetype A2 and has very low affiliation to A0 and A1 (2% and 3%, respectively). Thus, this cluster includes stop locations in commercial and industrial areas without connection to the TEN-T network or parking areas with other services. 25% of all 7,456 truck stop locations correspond to Cluster A.

Cluster B has 85% affiliation to A1 and 73% to A2. Thus, cluster B includes stop locations at parking areas with additional services in commercial and industrial areas. This affects 39% of all stop locations in the data set, which makes B the biggest cluster. Additionally, it covers 34% of all stops per day.

Cluster C has high affiliation values to archetypes A0 and A1 (70% and 87%) and moderately (42%) to A2. Thus, this cluster represents most stop locations along the TEN-T network with rest areas, parking areas and other services, partly located in commercial and industrial areas. We find, that only 9% of all stop locations belong to this cluster, but they still experience 14% of all daily stops. The average number of stops (7.3) is significantly higher than for clusters A and B (3.6 and 4.1).

Table 4: Cluster analysis of affiliation tuples

Average affiliations of clusters A to F to archetypes A0 (hosted rest areas along the TEN-T network), A1 (public truck parking lots with additional services such as toilet facilities or restaurants) and A2 (industrial and commercial areas). For each cluster, information about the respective number of stop locations corresponding to the cluster and the average number of stops at those locations indicate the importance of the cluster. Our data show three main clusters: A, B and C.

Cluster	Affiliation to Archetype			Number of Loca-tions	Number of Stops	Share of	
	A0	A1	A2			Locations	Stops
A	2%	3%	69%	1828	3.6	25%	19%
B	6%	85%	73%	2883	4.1	39%	34%
C	70%	87%	42%	664	7.3	9%	14%
D	75%	58%	4%	382	7.8	5%	9%
E	57%	2%	38%	311	2.5	4%	2%
F	68%	29%	4%	427	1.4	6%	2%
Total						87%	80%
Noise						13%	20%

Source: Own calculations.

Overall, the analysis shows that 87% of all stop locations belong to one of the six clusters and can be easily characterized by affiliation tuples. These stop locations experience 80% of all daily stops.

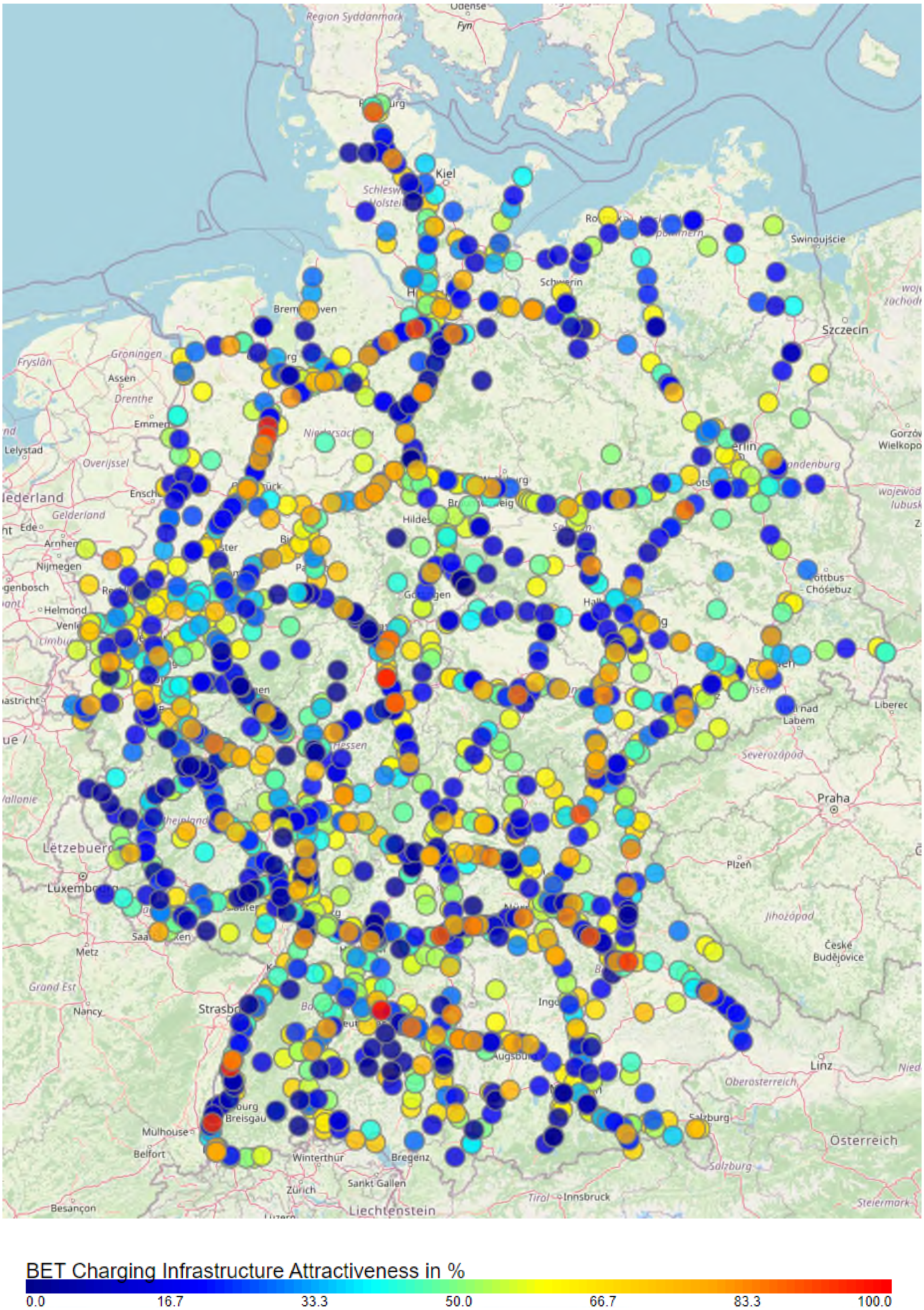
Clusters A and B already cover over 63% of all stop locations and over 53% of all daily stops. Together with Cluster C, over 76% of all stop locations and over 73% of all daily stops can be explained using our approach. Thus, the majority of stop locations are located either in commercial and industrial areas (A), in parking areas with other services and commercial and industrial areas (B) or along the TEN-T network with rest areas, parking areas, other services and partly in commercial and industrial areas (C). Having identified these usage patterns, we recommend those three archetypal clusters for the development of future charging infrastructure for BETs.

3.2 Attractiveness evaluation of public parking areas for future charging locations for BETs

In Germany, we find $p = 1.648$ potential public truck parking areas and evaluate their attractiveness for future charging infrastructure for BETs. Figure 5 visualizes those results using an HTML-based map and heat map. The HTML-based map shows all potential locations as small circles, color-coded by attractiveness. Figure 6 visualizes those results as a heat map on postal code area.

Figure 5: Attractiveness evaluation of potential truck parking areas in Germany

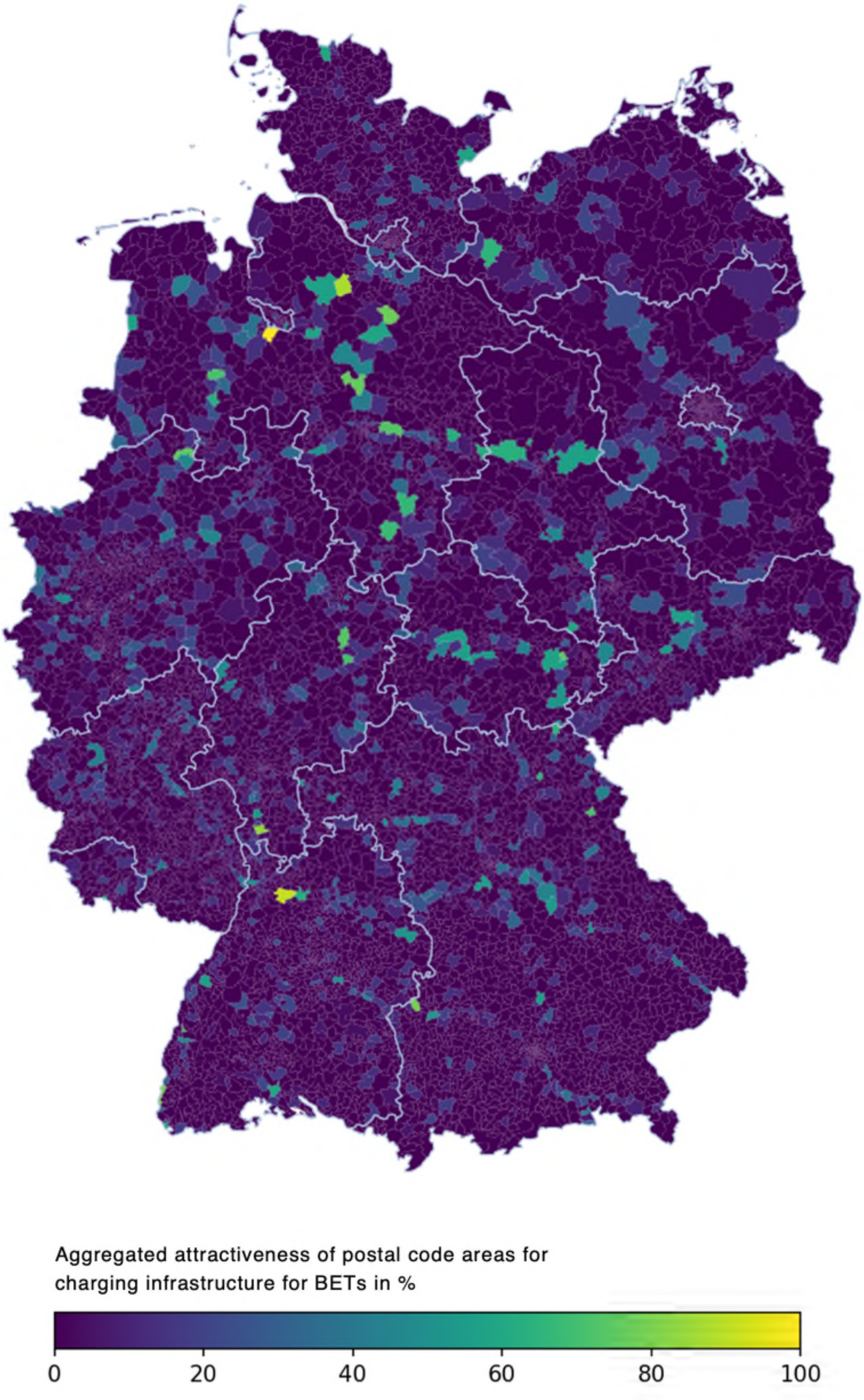
The attractiveness of p = 1648 potential truck parking areas for future BET charging infrastructure in Germany in%.



Source: Own calculations.

Figure 6: Attractiveness evaluation of postal code areas in Germany

Heat map of aggregated attractiveness per postal code area for future BET charging infrastructure in Germany in%.



Source: Own calculations.

4 Discussion

4.1 Evaluation

Derivation of feature weights based on real-world data

While related MCDA literature uses subjective assessment, this study benefits from real-world data for the derivation of the feature weights using the information on the average number of daily stops. Therefore, our results are not based on subjective assessments by authors or experts and instead reflect the actual usage patterns of trucks.

Easy adjustment of feature weights when evaluating future charging infrastructure locations

At the same time, when evaluating future charging infrastructure locations for BETs, there still is the possibility to easily adjust the previously derived feature weights based on personal opinions and to subjectify the results accordingly if needed.

Discrepancy between aerial vs. real-world road distance

Our distance matrix reflects the aerial distance for point-related features characterizing a truck stop location within a search radius of 2000 meters. Thus, we highlight the difference between aerial and real-world road distances.

Average number of stops per day vs. local traffic volume data

The average number of daily stops could be related to the traffic volume at the truck stop location. Locations along main roads will experience more daily stops than locations with identical features in a region with low traffic. Therefore, we used heavy-duty traffic volume data from counting stations along the highways (Bundesanstalt für Straßenwesen 2022) and matched the respective coordinates with our truck stop locations. However, we do not identify any relationship between the average number of daily stops and the traffic volume at the nearest counting station.

4.2 Limitation

Truck stop location data

We were not allowed to use the original data for our assessment but used the processed and published data by Plötz and Speth (2021). The resulting cluster centroids represent, so to say, fictive truck stop locations representing only a fraction of the original data. An alternative may be using the center of gravity per cluster. Regardless, we chose a large search radius and set the maximum relevant distance to over 500 meters.

Distance matrix calculation: point vs. surface

Our approach uses point-related vs. area-related information and we apply a static search radius of 2000 meters when setting up our distance matrix. For point-related features, we do not consider the underlying area expansion of those features. As a result, features with large areas, such as harbors, airports, or exhibition areas, are only represented by their center point, so the search radius could be too small. The presence of those features would thus be underrepresented in our analysis.

Loss of information by setting up a binary feature matrix

Since we use a binary matrix for our weighting, we lose all distance-related information. An alternative methodology would be calculating feature weights using a matrix of inverse distances. This would give more weight to those features which are particularly close to the truck stop locations.

Data on commercial and industrial areas for future charging infrastructure locations for BETs

Our data only includes potential locations for future public charging, and private or semi-private locations are not included. As a result, charging locations at commercial or industrial areas may be highly underrepresented in our assessment.

Expansion: Europe

Using the truck stop location data provided by ACEA, we could transfer our method to the scope of Europe. This would enable a Europe-wide analysis and highlight country-specific differences. However, this would require further GIS data sources, as some of the data used in this work only relate to Germany. The integration of these new GIS data sources would be complex, and the inhomogeneity of the data sources would increase.

Expansion: Additional features and non-public charging infrastructure

Additional features and GIS data, particularly those related to commercial and industrial areas, could help to improve this work, and provide more complex and reliable attractiveness results. Adding information about private and semi-public truck parking areas would expand the scope of this study beyond publicly accessible charging infrastructure.

Application of other methods and comparison

Other methods, such as a regression analysis based on Mortimer et al. (2022), could be advantageous. We could use the average number of stops per day as a dependent variable and implement the distance matrix as independent variables. The regression model results could then be compared to the feature weight rankings of this work.

5 Conclusion

The present paper aimed to characterize current truck stop locations by choosing a GIS-based multi-criteria analysis and assess the attractiveness of potential future truck stop locations for BET charging infrastructure. While related studies use weighting methods based on subjective weighting processes, this study benefits from real-world data for deriving the feature weights. Our results demonstrate the high attractiveness of industrial areas with many potential business destinations along the most important European highways (TEN-T network), which may occur as trivial at first sight. However, our results imply that no particular feature determines this or any other attractiveness of current truck stop locations. In contrast, it is rather the distinct feature.

To improve the understanding of the features and their dependencies, we used the archetypal analysis. The identified archetypal extremes may constitute the backbone of a German BET charging network and cover over 70% of all stop locations and daily stops. The three archetypal clusters are:

(A) Commercial and industrial areas with features such as workshops and shops.

(B) Parking areas with additional services close to commercial and industrial areas.

(C) Hosted rest and parking areas along the TEN-T network.

While clusters A and B represent the biggest shares of stop locations, cluster C proves its importance with a relatively high number of daily stops, which indicates a high expected utilization rate. Considering these existing usage patterns, we recommend those three archetypal clusters for the development of future charging infrastructure for BETs.

Finally, the attractiveness of 1,648 potential locations for public BET charging infrastructure was evaluated, which has not been conducted in any study before.

In summary, this paper and its methods serve as a comprehensive and useful framework to determine charging infrastructure locations for BETs.

6 List of figures

7 List of tables

8 Bibliography

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A.1 Annex: Data and Methods

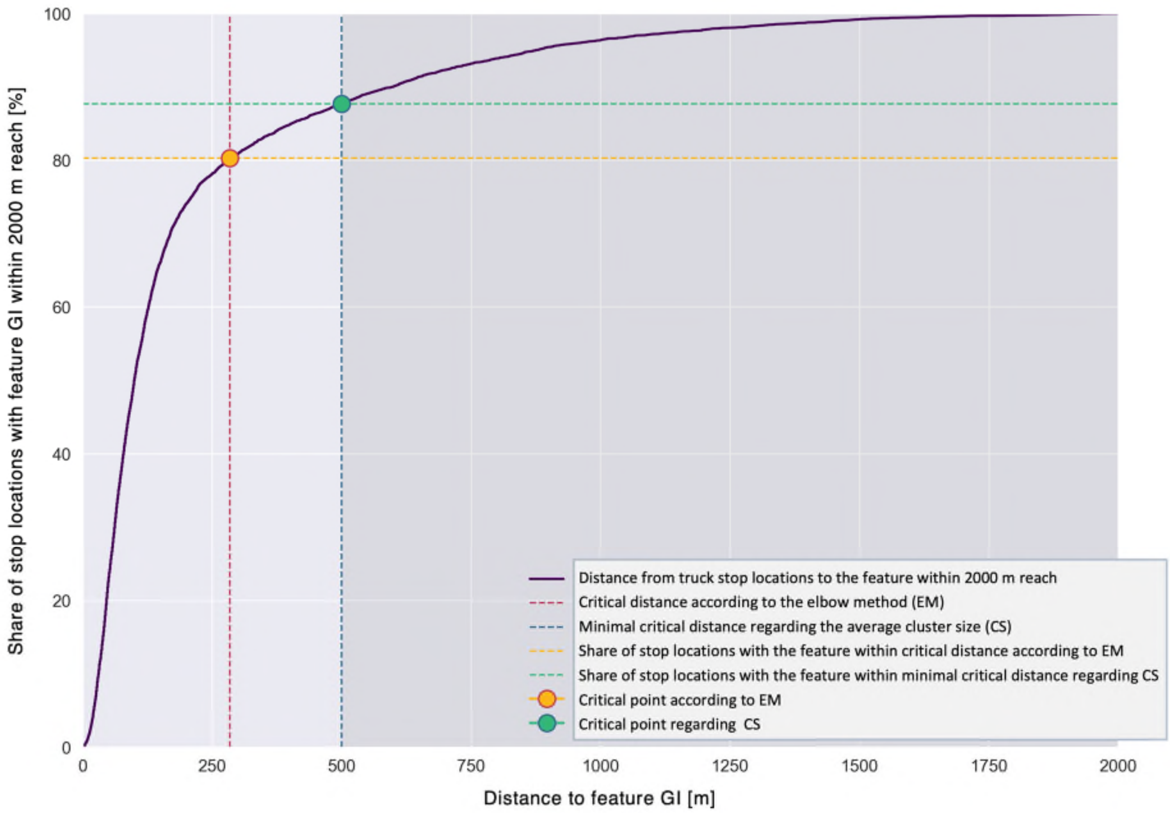
Elbow Method and Critical Distance

We identify a critical distance CD_j for each feature applying the "Elbow Method" (EM). This method is originally used in machine learning to determine optimal k for the k-means clustering algorithm (Cui 2020). The EM attempts to find the knee of a curve and is implemented in this work using the Python package "kneebow". For this purpose, we first sort the distance vector of all stops (stops without features within a 2000 m radius excepted) in ascending order for each feature j. Then, the elbow of the resulting curve indicates the respective critical distance CD_j.

Figure 7 shows this approach for the feature GI (commercial and industrial area) as an example: The curve visualizes the share of truck stop locations with the feature GI according to the distance from the stop location to the feature. As the curve follows an elbow shape, we can identify the elbow point, in this case $CD_{GI} = 284\, m$. This is the critical distance point according to the elbow method.

Figure 7: Distance between truck stop locations to feature GI (commercial and industrial area) when within 2000 m reach

Critical distance CD_{GI} according to the elbow method (EM) and final critical distance considering the average cluster size FCD_{GI}.



Source: Own calculations.

Limiting the minimum of this value to 500 m in order to take into account the average cluster size (compare Plötz and Speth 2021) results in determining a final critical distance FCD_j for each feature based on this critical distance CD_j according to the elbow method (compare equation 2). This is visualized in Figure 7 as well.

Both resulting values, critical distance CD_j and final critical distance FCD_j, are shown in Table 5 for all features:

Table 5: Critical distance CD_j and final critical distance FCD_j for all features in meter

Feature j	Critical distance CD_j	Final critical distance FCD_j
TT1	500	500
TT2	386	500
HA	443	500
BH	745	745
FH	324	500
GU	389	500
GI	284	500
ME	830	830
GM	419	500
PP	372	500
WC	270	500
RA	235	500
RE	574	574
TA	347	500
AH	610	610
HO	797	797
SH	476	500
WA	589	589
WS	550	550

Source: Own calculations.

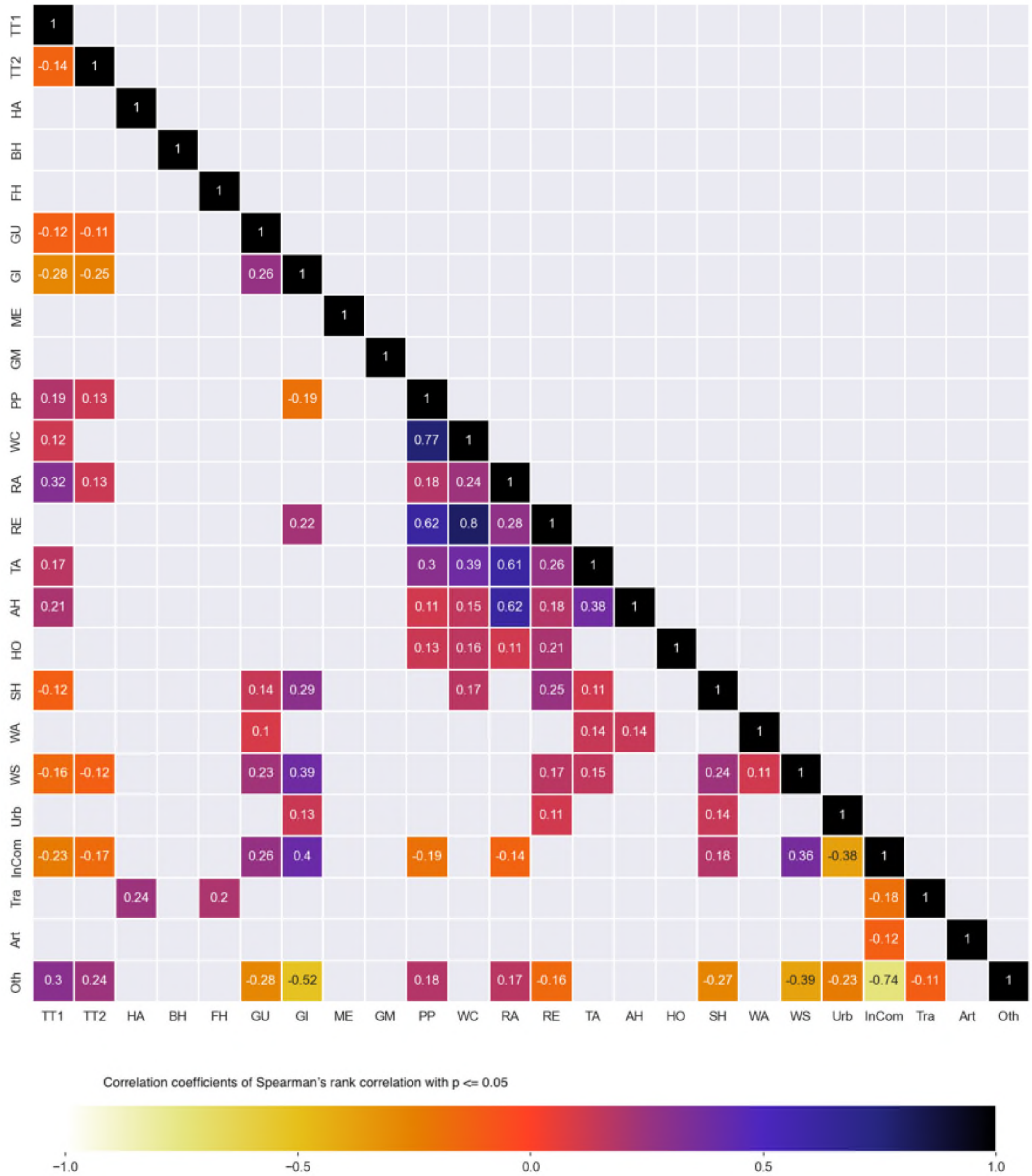
A.2 Annex: Results

Spearman's Rank Correlations

The results of Spearman's rank correlation show several moderate to strong correlations between features.

Figure 8: Significant correlation coefficients of Spearman's rank correlation

Only significant coefficients with p-values <= 0.05.



Source: Own calculations.