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Where to charge battery-electric trucks in Germany: A GIS-based statistical analysis using real-world truck data

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Executive Summary

While battery-electric trucks (BET) promise tremendous potential for reducing greenhouse gas emissions in road freight transport, their deployment necessitates an adequately developed charging infrastructure. Knowing the attractiveness of truck stop locations is crucial to ensure sufficient coverage and worthwhile charger installation and highlight potential demand for future efforts such as grid expansions as early as possible. Thus, this analysis aims to characterize current truck stop locations and derive the most suitable locations for BET charging infrastructure in Germany based on real-world truck data and GIS-based statistical analyses. Our results demonstrate that the attractiveness of any location is driven by multiple concurrent factors rather than one single factor. In addition, we derive three charging infrastructure archetypes that may constitute the backbone of a German charging network: (1) Large and high-traffic industrial areas such as industry hotspots, harbors, and airports; (2) Hosted rest areas or truck stops along the TEN-T network; (3) Industrial areas with designated truck parking areas, including hosting and services.

Keywords: electric vehicle, heavy-duty, truck, charging, infrastructure

1 Motivation

Mitigating anthropogenic climate change in line with the Paris Agreement and 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 [1].

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 [2, 3]. Thus, a steep market ramp-up is expected in the upcoming years [4]. However, one crucial factor for the widespread adoption of BETs is an adequately developed charging infrastructure to facilitate convenient and reliable operations in light of limited electric ranges [5]. This raises one central 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 the Alternative Fuels Infrastructure Regulation (AFIR) so that sufficient charging infrastructure for trucks along the most important European highways (TEN-T network) will be mandatory. This proposal includes, among others, minimum power requirements, a minimum number of charging points, and distance intervals within this network [6]. However, the concrete realization will be handed to the national authorities and private organizations. Exemplary, the National Centre for Charging Infrastructure (NLL) in Germany hosts the so-called "StandortTool" [7]. 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.

While charging infrastructure site selection is well documented and differentiated for passenger cars, insights for heavy-duty trucks are few or suffer from the trade-off between geographic coverage and level of detail. Metais et al. [5] and Pagany et al. [8] reviewed infrastructure modeling for general plug-in electric vehicles, highlighting differences in the used data types, different demand allocation approaches, different optimization problems, optimization targets, and further problem extensions. Additionally, Al-Hanahi et al. [9] highlighted key challenges and future work for charging infrastructures of commercial electric vehicles. Notable for heavy-duty trucks, T&E [10] and Speth et al. [11] used NUTS3-level freight-flow data to calculate potential traffic intensities and determine charging infrastructure locations along the TEN-T network. Similarly, Tong et al. [12] determined on-route charging locations along the US national highway network using freight-flow data and generalized truck movements. However, these broad conceptual networks have no precise location information, and the real-world conditions for selected locations are unknown, making the feasibility questionable. By contrast, the better availability of empirical data from passenger cars facilitates a higher level of detail, particularly using Geographical Information Systems (GIS) data. Mortimer et al. [13] 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. Kaya et al. [14] 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. Schmidt et al. [15] proposed a five-stage multi-criteria and GIS-based location methodology for urban areas covering similar categories and using a light beam search heuristic to constitute different service networks in Poznan, Poland.

In summary, while various approaches, well-known frameworks, and multiple assessments for passenger cars exist, detailed insights for trucks with special needs, such as extra parking and maneuvering space, distinct operational patterns, and higher power requirements are limited. Consequently, this paper aims to provide insights into the attractiveness of truck stop locations and determines potential charging locations. Findings may support a coordinated charging infrastructure deployment for trucks and help infrastructure providers find the most attractive locations, which entails high infrastructure profitability.

This paper is structured as follows. Section 2 describes the data and applied methods. The data section covers GPS truck stop data and data enhancement using different sources. Section 3 contains the results. This paper closes with a discussion in section 4 and conclusions in section 5.

2 Data and methods

2.1 Data

Truck stop data

This paper uses European truck stop data from the Association des Constructeurs Européens d'Automobiles (ACEA), including seven truck manufacturers (OEM) and heavy diesel trucks with over 7.5 tons of gross vehicle weight. This data have been analyzed by Plötz and Speth [16], where methods and details are documented. From over 750,000 GPS-based locations recorded over one year, using several filter criteria and the DBSCAN algorithm yielded $m^* = 34{,}227$ clustered locations covering stops from long-haul and regional trucks. Clusters contain at least three original locations. Usual cluster sizes range from 300 to 450 m. While data coverage for certain small European countries is limited, coverage for Central, Western, and Northern Europe is more representative [16]

Clustered data comprises the geographical location (latitude and longitude of the cluster centroid) and the average number of stops (nos) per day. This information is used to calibrate and weigh the attractiveness of locations, ensuring high practical relevance. The following results are limited to Germany, with processing $m = 8{,}308$ truck stop locations from regional and long-haul trucks.

Data enhancement

The data enhancement process assigns corresponding attributes to each stop location. Attribute selection is inspired by expert opinions and findings from similar studies, such as [13–15, 17], comprising socio-economic, geographical, traffic, road network, and POI data categories. Categories, corresponding attributes, and data types are listed in ***Table 1***. Five categories with $\mathrm{n} = 34$ attributes are combined to characterize each stop location.

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. This data is available for the EU, EFTA, and the UK.

The category *Traffic* incorporates information on the regional traffic volume represented by the total annual journeys inside the corresponding NUTS-3 area. The affiliation of any location to a NUTS3 region is unambiguous. This information is derived from two datasets provided by Eurostat [18]: (1) Annual road freight transport by region of unloading (road_go_ta_ru); (2) Annual road freight transport by region of loading (road_go_ta_rl). For each country, numerical values are rescaled with the maximum and minimum so that all values are between 0 and 1. Accordingly, 1 indicates the highest trip-intensity level inside a country and 0 the lowest. We use 2020 as the reference year as it is the last complete year, incl. the UK.

The category *Urbanization* incorporates information on the degree of urbanization, providing insights into socio-demographic factors. Based on the DEGURBA dataset provided by Eurostat [19], we differentiate between three areas: (1) cities and densely populated areas; (2) towns, suburbs, and intermediate-density areas; (3) rural and thinly populated areas. The affiliation of any location to a DEGURBA class is 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) [20]. While the original data distinguishes between 38 labels, we aggregate similar labels and then distinguish only 7: (1) Urban areas; (2) Industrial and commercial areas; (3) Transport areas such as airports, port areas, and transport-associated land; (4) Mine, dump and construction sites (MDC); (5) Agricultural areas such as arable land and pastures; (6) Natural areas such as forests and semi-natural areas; (7) Other areas. The affiliation of any location to a CLC class is unambiguous. We use 2018 as the latest available reference year.

The category *POI* incorporates information on specific conditions at the respective location, thus characterizing the location more precisely. This information is based on the PTV Developer Geocoding API [21] that combines several other data sources, such as data from HERE Technologies. This commercial data source was used under the Freemium model, allowing up to 100,000 free queries per month. The maximum search radius is set to 2000 m, and the maximum number of returns is 50 items. While the original data distinguishes between 438 POI labels (so-called navteq-lcms items), we aggregate similar labels and then distinguish only 22 POI labels: (1) Accommodations such as hotels or motels; (2) Attractions such as sights, natural and geographical attractions, and leisure and outdoor facilities; (3) Automotive businesses such as repair services, dealerships, and service facilities; (4) Federal or public businesses such as police and ambulance; (5) Retail businesses such as groceries, shops, and stores; (6) Commercial businesses or service providers; (7) Consumer businesses or service providers; (8) Truck businesses such as repair services, dealerships, and service facilities; (9) Restaurants; (10) Entertainment venues; (11) Facilities such as hospitals, sports venues, and community facilities; (12) Fueling stations; (13) Large industries; (14) Parking areas; (15) Rest areas with full service covering restroom facilities, parking, and shops; (16) Rest areas with limited service; (17) Cargo transport facilities such as warehouses, distribution centers, and courier services ; (18) Cargo airport areas; (19) Seaports and container terminals; (20) Public transport offers such as bus or train stations; (21) Truck parking with designated area for parking heavy trucks; (22) Truck stops. One location may have several POI labels. More details can be obtained from the API documentation.

Table 1: Attributes for truck stop location characterization

Category	**Attribute (short)**	**Variable**	**Unique classification**	**Info**
Road Network	TEN-T Core Network	tt_{Core}	x	Num. distance in m
	TEN-T Compr. Network	tt_{Comp}	x	Num. distance in m
Traffic	Traffic volume	ti_{N3}	x	Num. value
Degree of Urbanization	City	$urba_1$	x	Binary
	Town, Suburbs	$urba_2$	x	Binary
	Rural	$urba_3$	x	Binary
Landuse	Urban Fabric	clc_{Urb}	x	Binary
	Transport	clc_{Tra}	x	Binary
	Natural	clc_{Nat}	x	Binary
	MDC	clc_{MDC}	x	Binary
	Industrial, Commercial	clc_{IC}	x	Binary
	Agricultural	clc_{AG}	x	Binary
POI	Accommodation	poi_{Acc}	-	Num. distance in m
	Attractions	poi_{Att}	-	Num. distance in m
	Business Automotive	poi_{BA}	-	Num. distance in m
	Business Federal / Public	poi_{BFP}	-	Num. distance in m
	Business Retail	poi_{BR}	-	Num. distance in m
	Business Commerical	poi_{Com}	-	Num. distance in m
	Business Consumer	poi_{Con}	-	Num. distance in m
	Business Truck	poi_{Tr}	-	Num. distance in m
	Restaurants	poi_R	-	Num. distance in m
	Entertainment	poi_E	-	Num. distance in m
	Facilities	poi_F	-	Num. distance in m
	Fueling station	poi_{FS}	-	Num. distance in m

	Industry	poi_I	-	Num. distance in m
	Parking	poi_P	-	Num. distance in m
	Rest area (full service)	poi_{RA1}	-	Num. distance in m
	Rest area	poi_{RA2}	-	Num. distance in m
	Transport Cargo	poi_{TC}	-	Num. distance in m
	Transport Cargo Airport	poi_{TCA}	-	Num. distance in m
	Transport Cargo Harbour	poi_{TCH}	-	Num. distance in m
	Transport Public	poi_{TP}	-	Num. distance in m
	Truck Parking	poi_{TrP}	-	Num. distance in m
	Truckstop	poi_{TrS}	-	Num. distance in m

Further attributes are required to reflect particularities for charging infrastructure. Thus, we include an additional category that represents *Energy Supply*. This covers two aspects, summarized in ***Table 2***: (1) The availability of surrounding grid substations to represent a potential expansion cost minimization. Geo-coordinate information is derived from OpenStreetMaps (OSM) using the overpass-API. The distance of any location to the nearest substation is calculated as an aerial distance (haversine formula) and, thus, unambiguous. We limit the query to stations with available power-level information and cut off at the distribution grid level. (2) The availability of existing high-power charging infrastructure (HPC, over 50 kW) for passenger cars to represent a potential utilization of synergies. Information is derived from OpenChargeMaps (OCM) for general coverage. To support this, we use the charging station register provided by the Bundesnetzagentur [22] as a country-specific data source. The distance of any location to the nearest HPC is calculated as an aerial distance (haversine formula) and, thus, unambiguous. As a result, six categories with $n^* = 36$ attributes are combined to characterize the attractiveness of potential public charging locations.

Table 2: Additional attributes for charging locations

Category	**Attribute (short)**	**Variable**	**Unique classification**	**Type and Unit**
Energy supply	Substation	ec_{Sub}	x	Num. distance in m
	HPC for cars	ec_{HPC}	x	Num. distance in m

Potential public charging locations

Potential public charging locations are based on three different datasets: (1) We derive all parking locations from OSM, resulting in 523,340 potential locations. This data is filtered, so only truck-accessible and non-private parking areas with over 200 m² remain. This yields 2,716 potential locations. (2) We derive all rest area and road service locations with over 200 m² from OSM, resulting in 1,912 potential locations. (3) We use 2,217 highway rest area locations provided by the NOW GmbH.

The final public charging locations are determined by merging these three datasets. Therefore, we use the DBSCAN algorithm to avoid duplicates (e.g., not exactly matching geo-coordinates for the same location) and combine charging locations (e.g., on opposite street sides). The maximal cluster distance (epsilon parameter) is set to 500 m, the minimal number of points in a cluster (minPts parameter) is set to 1, and border points are included. This yields $p = 2{,}137$ potential locations.

2.2 Method

Our multi-criteria and GIS-based assessment involves five steps and follows, in general, the process from Kaya et al. [14]. All process steps are explained below, and all calculations are executed with Python.

Phase 1: Characterization of current truck stop locations

First, we set up the $m \times n$ matrix D containing the information on each feature $j \in \{1,..,n\}$ for each actual truck stop location $i \in \{1,..,m\}$.

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

For the feature categories *Urbanization* and *Landuse,* this information is binary, meaning that a one indicates that this feature matches, and a zero indicates that it does not.

For the remaining categories, we assume that the closer a feature is to the truck stop location, the stronger its influence is. Thus, a feature in the immediate neighborhood of the truck stop location has the strongest influence, while this vanishes with distance. We impose a maximum relevant distance d_j to limit the effective range of any feature and thus prevent data noise. Assuming a linear characteristic, the effective impact d_{ij} of each feature j on each truck stop location i is calculated by:

$$d_{ij} = \frac{d_j - dist(x_{ij})}{d_j}, d_{ij} \in \{0,..,1\} \text{ for i} \in \{1,..,m\} \text{ and j} \in \{1,..,n\} \quad (2)$$

This maximum relevant distance per feature d_j is calculated using the elbow method heuristic and all $m^* = 34{,}227$ truck stop locations. We calculated the minimum distance from each truck stop location to the TEN-T Core / Comprehensive Network for the *Road Network* category. For the *POI* category, all possible returns from the PTV API (cf. max 50 items within a 2000 m radius) are collected for each stop location. Finally, all distances from all stop locations are merged and 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. This method determines where the ECDF has its maximum curvature, representing the distance from which the incremental benefit per additional relevant distance decreases. This value ranges from 290 to 1,200 m. However, depending on the ECDF curvature, results may be inaccurate. Therefore, we use the 80 percent threshold distance $\left[f_{ECDF,j}^{-1}(0.8)\right]$ as an alternative value. This value ranges from 250 to 1,470 m. One of these two methods determines the value for $d_{knee,j}$. To reflect uncertainty regarding cluster size and centroid (cf. Section 2), we set the minimum value to 500 m. Thus, the maximum relevant distance d_j is calculated as follows:

$$d_j = \max\left(d_{j,knee}, 500\right) \, in \, m \, for \; \text{j} \in \{1,..,n\} \quad (3)$$

The maximum relevant distance ranges from 500 to 1050 m across all features. ***Figure 1*** visualizes the procedure for the category *POI Fueling Station* (left, maximum relevant distance = 700 m, blue line) and *Truck Parking* (right, maximum relevant distance = 880 m, gray line).

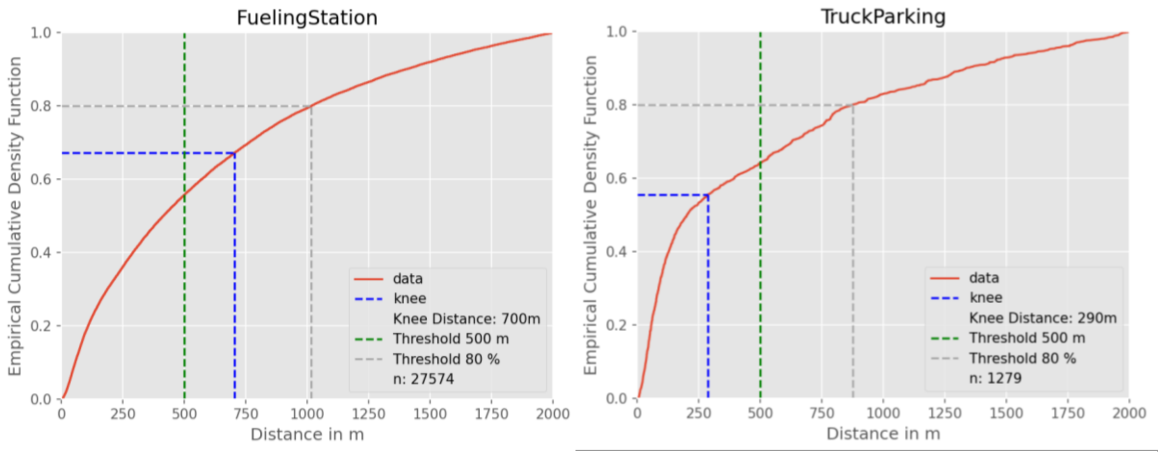

Figure 1: Determination of the maximum relevant distance per feature. Own illustration.

Phase 2: Statistical analysis

Given our $m \times n$ matrix D, we use the archetypal analysis to identify extreme observations (so-called archetypes) in this matrix and, thus, capture heterogeneity among observations. Accordingly, this statistical analysis helps to improve the understanding of the features and their dependencies. As a result, all the observations may be reproduced as mixtures (linear combinations) of those extremes. This contradicts typical cluster analyses that rather homogenize these observations. These archetypes are selected by minimizing the squared error of each observation as a mixture of archetypes using the Python package [23].

Phase 3: Weighting process

For the weighting process, we use the average number of stops nos_i for each truck stop location $i \in \{1,..,m\}$ for empirical weighting. These weights quantify the importance of parking characteristics for truck stop locations and enable a feature ranking. This contradicts typical subjective MCDA methods such as AHP, PROMETHEE, or VIKOR to determine such weightings. Accordingly, we calculate the standardized sum product based on the feature matrix D and the average number of stops for each truck stop location. That said, the weight w_j of each feature is calculated as follows:

$$w_j = \frac{\sum_{i=1}^{m} d_{ij} \cdot nos_i}{\sum_{j=1}^{n} \sum_{i=1}^{m} d_{ij} \cdot nos_i}, \qquad j = 1,2,\ldots,n \tag{4}$$

Phase 4: Attractiveness of potential public charging locations for future truck charging locations

Last, we use these feature weights for each potential charging infrastructure location $k \in \{1,..,p\}$ and apply the weighted sum method (WSM) to determine an attractiveness score for each location. As empirical weighting was impossible for the category *Energy Supply*, we assume suitable weights by setting the mean value from w_j. Likewise, the maximum relevant distance is assumed with 750 m. This results in the following adjusted formula for calculating the score S_{i^*} of a parking location:

$$S_{i^*} = \sum_{j=1}^{n^*} w^*{}_j \cdot d_{kj}\,, \quad for\ k \in \{1,..,p\} \tag{5}$$

with

$$w^*{}_j = \frac{w_j}{\sum_{j=1}^{n^*} w_j}, \qquad j = 1,2,\ldots,n^* \tag{6}$$

3 Results

The result section covers three sections: the calculated feature weight, the archetypal analysis results, and the potential locations' final attractiveness.

3.1 Feature weights and ranks of feature importance

Table 3 shows the importance of parking characteristics and the feature ranking based on the weighing process. Scores range from almost 0 to 10.1 percent. The top 10 features are highlighted with a cut-off value at 4.3 percent. The mean value is 2.9 percent, whereas the median is 1.7 percent. It follows that industrial areas with many potential business destinations along the TEN-T Core Network are most suited. We highlight that 23 features have weights above 1 percent, indicating the wide spread of feature weights and large heterogeneity.

Table 3: Feature weights and ranking

Variable	tt_{Core}	tt_{Comp}	ti_{N3}	$urba_1$	$urba_2$	$urba_3$	clc_{Urb}	clc_{Tra}	clc_{Nat}	clc_{MDC}	clc_{IC}	clc_{AG}	
Score in %	5.3	2.0	2.6	3.8	7.0	4.2	0.8	1.0	1.7	0.1	8.3	3.0	
Rank	7				5						3		
Variable	poi_{Acc}	poi_{Att}	poi_{BA}	poi_{BFP}	poi_{BR}	poi_{Com}	poi_{Con}	poi_{Tr}	poi_{R}	poi_{E}	poi_{F}	poi_{FS}	poi_{I}
Score in %	0.3	0.5	6.6	1.2	7.1	10.1	10.1	1.3	2.4	1.3	4.6	4.3	1.6
Rank			6		4	1	2				8	9	
Variable	poi_{P}	poi_{RA1}	poi_{RA2}	poi_{TC}	poi_{TCA}	poi_{TCH}	poi_{TP}	poi_{TrP}	poi_{TrS}				
Score in %	0.3	0.2	0.0	4.3	0.1	0.2	2.6	0.7	0.3				
Rank				10									

3.2 Archetypal analysis

Figure 2 shows the results from the archetypal analysis. Given the particular feature relevance as indicated by the color scale, we highlight three archetypes: (A1) Regions with high traffic volume resulting from large businesses, industries, or transport facilities, such as cargo airports or seaports, along the TEN-T Network; (A2) Hosted rest areas and truck stops along the Ten-T Network, ideally close to business entities and at suburb metropolitan areas; (A3) Industrial areas with a wide range of services and stores and designated truck parking areas. In contrast, the others archetype functions as a composite of other relevant features.

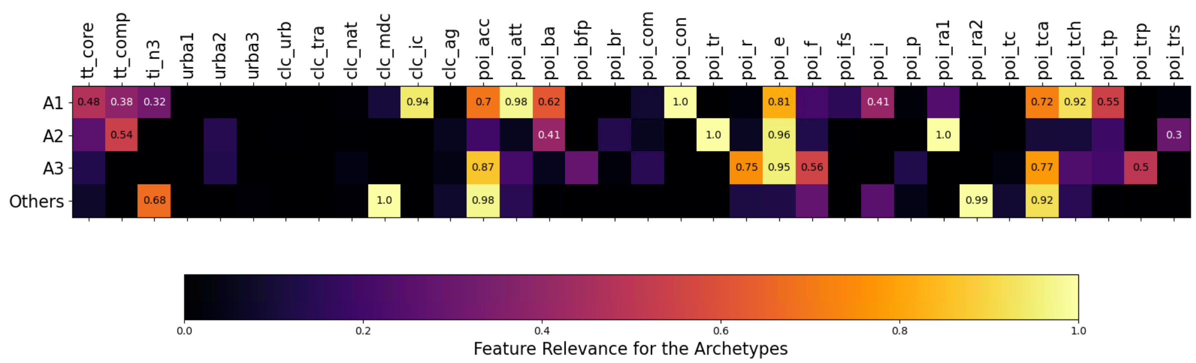

Figure 2: Archetype vectors with the respective feature specifications. Own illustration.

3.3 Attractiveness of public parking areas for future charging locations for BETs

Figure 3 visualizes the distribution of the relative attractiveness score of 2,137 potential locations in Germany as a boxplot. The distribution is skewed, and many locations have low to medium attractiveness. The median is 24.8 percent, the average value is 30.3 percent, and the standard deviation is 21.8 percent. Additionally, ***Figure 4*** visualizes all locations as an HTML-based map. This map contains all locations as small circles and their color-coded attractiveness. The zoom focuses on Baden-Wuerttemberg to underpin the level of detail.

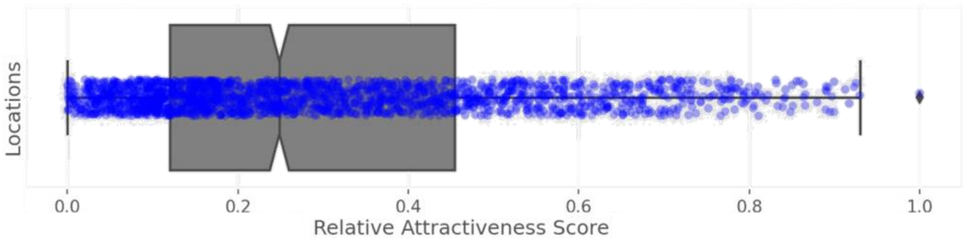

Figure 3: Boxplot of the relative attractiveness score. Own illustration.

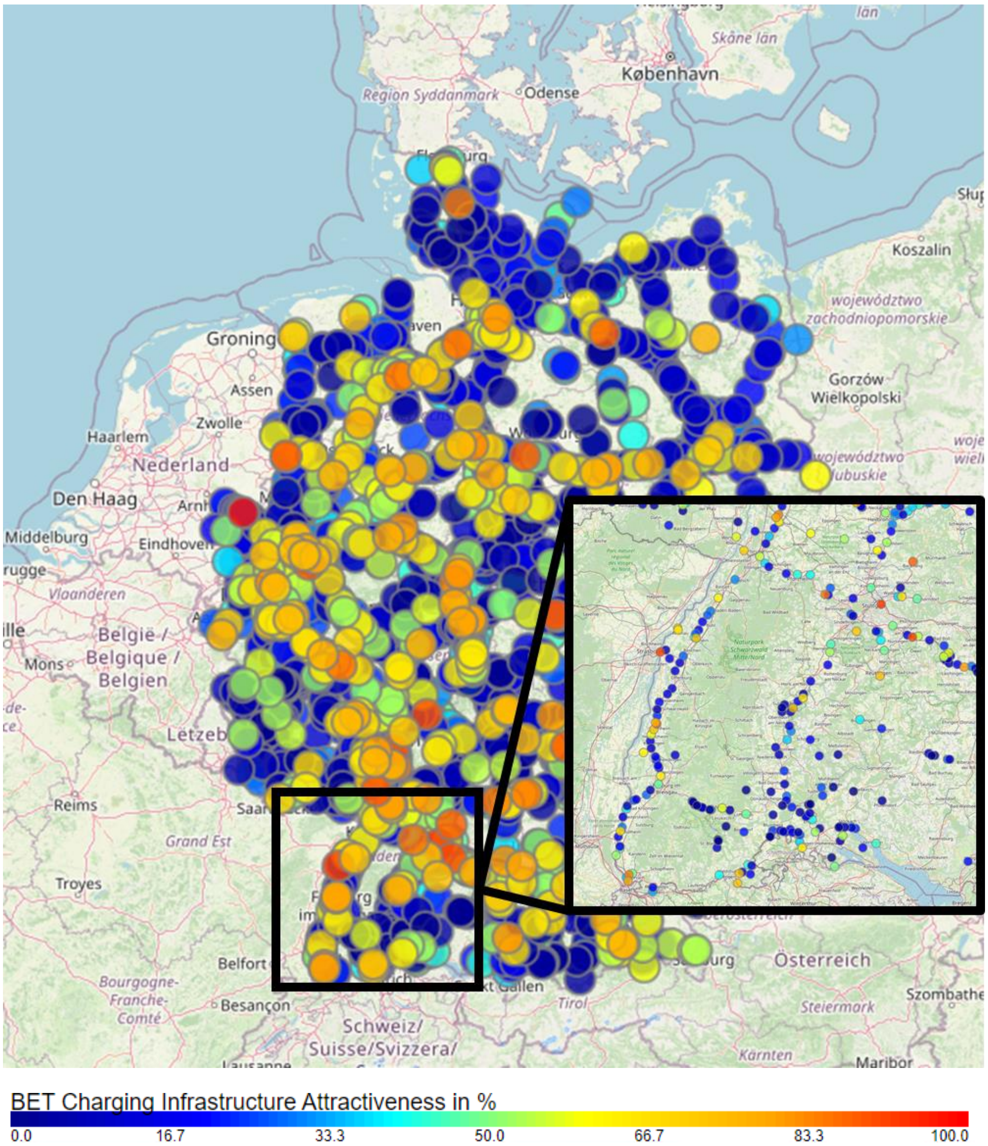

Figure 4: Attractiveness evaluation of potential truck parking areas in Germany. Own illustration.

4 Discussion

The present paper aimed to characterize current truck stop locations and derive the most suitable locations for BET charging infrastructure. While we used real-world data to ensure high practical relevance, we state that our results embed some uncertainty and acknowledge some limitations.

We were not allowed to use the original data for our assessment but used the processed and published by Plötz and Speth [16]. 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 m. Here, we note the difference between aerial and real-world road distances.

Our method uses a matrix that combines binary and distance-based variables. Since we only consider the relevance of the nearest feature, information about how many features are present is lost. Our assessment uses rather simple methods instead of more complex ones, such as neural networks or decision trees, to uncover new relations. Plus, one might determine the feature weighting with an optimization approach by using the feature weights as optimization variables to maximize the correlation between the predicted and actual average number of stops for all truck stop locations.

Our approach uses many different data sources and merges heterogeneous data types. The latter comprises, among others, point-related vs. area-related information or different spacial dimensions among the features. While other attributes may be added, information on data completeness per source is missing. Last, we used publically available data, but certain information is generally not publically available. This comprises, for instance, the information on available truck parking lots or the available local power grid capacity. Last, we highlight that we only considered potential public charging locations and no private locations.

Last, the analysis could be expanded to Europe since special emphasis is given to ensure that all data sources are available at the European level. However, this broader study would exceed the scope of this conference paper, focusing on methodology and data enhancement. Plus, the current approach ignores interdependencies between sites. That said, it is reasonable that in areas with a high density of potential sites, not all sites may be equipped with charging infrastructure. Thus, identified sites may also be combined with other optimization or localization approaches, such as [11], to ensure coverage. Accordingly, this analysis is only the first high-level analysis, and a detailed assessment by the local charging infrastructure operator must happen.

5 Conclusion

The present paper assessed the attractiveness of current truck stop locations by choosing a GIS-based multi-criteria analysis to determine the most important attributes. 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 combination that determines attractiveness.

To improve the understanding of the features and their dependencies, we used the archetypal analysis so that all observations may be reproduced as mixtures of those extremes. These extremes may constitute the backbone of a German BET charging network, covering industry hotspots, hosted rest areas or truck stops along the TEN-T network, and industrial areas with designated truck parking areas.

Finally, the attractiveness of 2,137 potential locations for public BET charging infrastructure was evaluated, which has not been conducted in any study before. Apart from location planning, station sizing and defining power requirements remain unanswered. In summary, this paper and its methods serve as a comprehensive and useful framework to determine charging infrastructure locations for BETs.

Acknowledgments

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