Influential Factors on Drivetrain Consumption in Electric City Buses and Assessing the Optimization Potentials

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Abstract: In response to the growing need for sustainable mobility amidst global challenges like climate change and urbanization, ensuring energy-efficient operation of Electric City Buses (ECBs) is crucial. This study initially utilizes techniques associated with explainable artificial intelligence, such as SHapley Additive ExPlanations (SHAP), to determine the impact of various factors such as vehicle speed, acceleration, braking on drivetrain consumption. The data is categorized into distinct scenarios such as acceleration, starting, curve, uphill and downhill for this analysis. In driving scenarios such as curves, uphill, or downhill, the position of the brake pedal, along with the accelerator pedal and vehicle speed, were identified as significant factors affecting drivetrain consumption. Secondly, the study delves into analyzing driving behavior during bus stop entries, employing methods like Deep Autoencoder-based Clustering (DAC) and Self-Organizing Map (SOM). In the results of the DAC and SOM analysis, it was found that Cluster 2, identified through the DAC model, exhibited substantial energy consumption, characterized by higher acceleration and lesser brake pedal usage. Conversely, the SOM analysis showed that the orange and blue clusters have greater energy efficiency, with a higher distance covered and lower energy consumption, contrasting with other clusters that consumed more energy for reaching the busstop.

1 INTRODUCTION

Given the challenges posed by global warming, population growth, and urbanization, the automotive industry faces mounting demands to foster more sustainable mobility. Electrifying vehicles offer a promising solution to mitigate greenhouse gas emissions in transportation. An increasing shift can also be observed in public transportation, where diesel-fueled buses are being replaced by electric city buses (ECB) (Mahmoud et al., 2016). ECBs now account for up to 4% of all new bus registrations in Europe, where electric bus registrations have been rising steadily since 2016 (IEA, 2021). In 2021, for the first time, three European countries registered more than 500 e-buses, with Germany leading the way with 581 units, followed by the UK with 540 units and France with 512 (SustainableBus, 2023). By 2022, nearly 66,000 electric buses and 60,000 medium and heavy-duty trucks will have been sold worldwide, representing about 4.5% of all bus sales and 1.2% of truck sales worldwide (IEA, 2023). At the same time, the transport companies already have concrete plans to produce around 6,600 more e-buses by 2030.

The energy consumption of an ECB consists of many components, namely drivetrain, heating, ventilation and air conditioning (HVAC), 24V Auxiliary, and Air compressor. The top two consumers are the drivetrain and HVAC (Rösch et al., 2023). An essential aspect of energy consumption estimation is considering the impact of driver's range anxiety, particularly the avoidance of driving with minimal energy remaining in the battery. It is important to note that the actual energy consumption of electric buses varies considerably depending on factors which are not directly controllable or alterable, such as passenger load, weather and traffic conditions However, driving style, which can be adjusted and optimized, offers an avenue to improve energy efficiency in electric buses. Utilizing the real world fleet data helps in identifying possibilities for energy efficient oper-

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ation for the top consumers such as drivetrain and HVAC (Sommer et al., 2023).

This research paper aims to investigate the various factors that impact drivetrain consumption in electric city buses and explore the opportunities for optimizing energy efficiency. By analyzing real-world data, and considering relevant parameters, this work aim to provide valuable insights into the key determinants of drivetrain consumption in ECBs. Furthermore, this study will assess how different driving styles, particularly scenarios like bus stop approaches, influence drivetrain efficiency. By examining these interactions, we aim to identify strategies for optimizing drivetrain performance in electric city buses.

2 BACKGROUND

2.1 Explainable Artificial Intelligence

Explainable Artificial Intelligence (XAI) aims to enhance the transparency of AI systems, moving away from opaque "black box" models towards algorithms that provide interpretable insights into decision-making processes. XAI seeks to make AI systems clearer and more trustworthy by offering explicit explanations that outline their capabilities, limitations, and behaviors in unfamiliar situations.The SHAP method (SHapley Additive ExPlanations), rooted in cooperative game theory and specifically Shapley values, measures the impact of each input feature on a model's prediction. It calculates Shapley values by considering all possible combinations of features, assessing their effect on the prediction. These values highlight the importance of each feature, with positive values indicating beneficial contributions and negative ones showing negative effects (Lundberg and Lee, 2017).

2.2 Deep Autoencoder-Based Clustering

Deep Autoencoder-based Clustering (DAC) (Lu and Li, 2021) is a generalized data-driven framework to learn to cluster representations using deep neuron networks. The methodology described in the study by Lu et al. involve training a deep autoencoder, consisting of an encoder and a decoder, using a provided training set. They initiated the process with a flattened input vector fed into a three-layer deep encoder, which is crucial for obtaining a low-dimensional learned representation. This representation was then reconstructed to its original dimensions by the decoder. Once their auto-encoder was adequately trained, it was used to produce a low-dimensional representation of the input data, which was then employed as input for the K-Means clustering algorithm to establish the required clusters in the data.

2.3 Self-Organizing Map

Kohonen's SOM (Kohonen, 1990) algorithm was employed in this study to model the dataset. It is an artificial neural network algorithm that operates on the principles of competitive learning. In SOM, an initial grid of neurons is established, each initialized with random vectors matching the input data's dimensions. During training, input data points are presented randomly to these neurons, with each neuron competing to become the Best Match Unit (BMU) by calculating its distance to the input. The BMU and its neighboring neurons adjust their codebook vectors based on a learning function. This process is repeated over the entire training set, resulting in centroids dispersed throughout the data space. After training, the nodes can be visualized in a grid structure, that helps in understanding the relationships and patterns.

3 RELATED WORK

Although ECB are environmental-friendly and able to benefit the development of a sustainable urban transit system, an important concern is energy consumption estimation that relates to driver's range anxiety—avoid driving with little energy remaining in the battery. In recent years, numerous researches have focused on developing more energy-efficient driving styles (Zhang et al., 2019; Kivekäs et al., 2019; He et al., 2021) and assistance systems to enhance the performance of an ECB. In a simulation study, a two-part strategy was developed in determining an optimal velocity interval (30-40 km/h) and an energy-saving acceleration mode, which resulted in a reduction of energy consumption by 2.47% overall in a bus trip in the simulation (Zhang et al., 2019). On the other hand, in this study efficient design choices were suggested to reduce the energy consumption (Kivekäs et al., 2019).

ECB's energy consumption is influenced by several factors, including road geometry, land use, weather, and vehicle conditions, as well as the driving behavior. Although vehicle conditions, weather, land use, and road geometry are typically constant factors within a predefined bus route, the driving style can vary among different drivers.

Predicting the energy consumption or determining the influencing factors are divided into two types, named as macroscopic and microscopic approaches

(Chen et al., 2021). The macroscopic approach focuses on developing models that predict energy consumption for longer distances of operation (Varga et al., 2019; Zhang et al., 2020; Thorgeirsson et al., 2021). It aims to estimate the overall energy consumption of an electric vehicle for the whole trip of operation. Additionally, this approach is utilized to predict the remaining range that will be covered by the vehicle, providing valuable information for planning and optimization. These studies have utilized influential factors, related to vehicle design, driver-related parameters, and environmental conditions as well.

The microscopic approach primarily focuses on the prediction of instantaneous energy consumption, which deals with second by second basis of the consumption (Zhang and Yao, 2015; De Cauwer et al., 2017; Beckers et al., 2020). This methodology also incorporates a wide array of factors, including driving conditions, vehicle speed, acceleration, and the activation of auxiliary systems. By taking these variables into consideration, the microscopic approach offers insights into the energy consumption patterns and dynamics exhibited by electric vehicles during their real-time operation.

4 METHODOLOGY

The methodology adopted in this study is structured into two distinct phases. The initial phase focuses on identifying the factors that significantly impact drivetrain consumption, specifically in certain scenarios. Subsequently, the second phase analyzes the driving behavior and consumption patterns as buses approach and enter the bus stops.

To determine the main influencing factors for the power consumption in the bus, a 1D-Convolutional Neural Network model (cf. (Kiranyaz et al., 2021)) was trained to predict the energy consumption for the next time step from various input signals. The trained model was then analyzed using SHAP to extract the various influencing factors on the drivetrain energy consumption (cf.Figure 1).

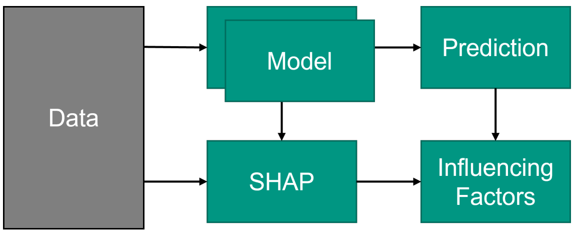

Figure 1: Workflow of getting the influencing factors of the drivetrain.

Table 1: Criteria for the seven scenarios to identify the influencing factors of the drivetrain.

Scenario	Group	Acceleration x-Direction $[m/s^2]$	Acceleration y-Direction $[m/s^2]$	Height Difference $[m]$	Brake Pedal $[\%]$	Accelerator Pedal $[\%]$	Vehicle Speed $[km/h]$
Acc	1	> 0.2				> 0.01	< 15
Starting	1	> 0			< 5	> 0.01	< 15
Curve	2		> 0.7				> 5
Uphill	2			> 0.01			> 0.00
Downhill	2			< -0.01			> 0.01

The pipeline, we used to prepare the data and train the model, is based on the CRISP-DM process (Wirth and Hipp, 2000). The data used for the training and prediction are measurement data collected utilizing onboard data collectors installed in electric city buses. In the data preparation stage, the dataset was partitioned into separate subsets for subsequent analysis, and individual trips within the time series data were identified by utilizing GPS coordinates of the depot location. This identification was crucial for isolating discrete journey segments, subsequently leading to a comprehensive feature selection process. The relevant features were selected, removing highly correlated signals and signals irrelevant to get the influencing factors of the drivetrain. We trained a model with the following input features to predict the drivetrain energy consumption:

- Brake torque
- Ignition state
- Total distance
- Speed
- Brake pedal
- Accelerator pedal
- Vehicle weight
- Remaining range
- Cruise control
- Current gear
- Air temperature inside
- Air temperature outside
- Steering wheel
- Battery voltage
- Retarder level
- Current energy consumption
- Battery isolation resistance
- Road level
- Inverter 1/2 power
- Low voltage output power
- Acceleration in x/y
- left/right turn signal
- Actual high voltage power
- Brake system malfunction
- Stop request
- Horn

The last 5 seconds were used as the time window for the input signals. The label value for the model is the current power value of the drivetrain consumption. Considering the whole dataset, 70% of the data is used as training, 20% is used for validation, and 10% is used for testing the model. Before training the model, the different windows of the training data were balanced.In doing so, the naturally underrepresented (very high and very low values cf. Figure 2 orange) energy consumption is oversampled; for this purpose, the underrepresented data samples are repeated in the data (cf. Figure 2 blue). Thereby an equal distribution of the training windows across all energy consumption is achieved (cf. Figure 2).

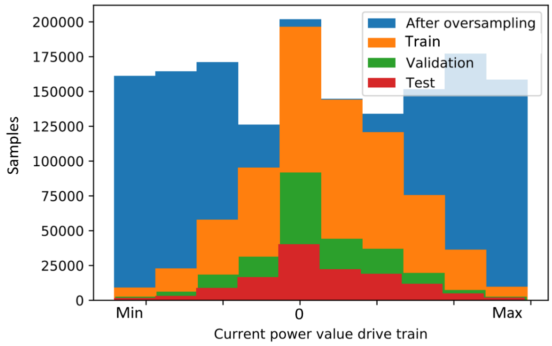

Figure 2: Histogram of the Train (before and after oversampling), Test and Validation Data.

For the explanation of the evaluation step, the data has been categorized into five scenarios to determine the influencing factors and to avoid comparing dissimilar situations (cf. Table 1). In this study, we have organized the scenarios into two groups to facilitate a clearer presentation of results (cf. Table 1). The scenarios of the first group differ essentially in the initial speed of the vehicles. Whereby the scenarios of the second group only differ in their form of driving.

For each of the five scenarios, heatmaps based on GPS coordinates were generated to identify locations with frequent occurrences. The five locations with the highest concentration of data points were further investigated. Data from these locations were processed and aggregated into separate datasets for each scenario. These datasets were then analyzed using SHAP values to identify key influencing factors.

In the second phase of the driving behavior analysis, focused on bus stop entry. Initially, timestamps for entering bus stops are determined after a trip reduction phase using specific signals such as GPS coordinates, vehicle speed, and door status. These signals serve as key criteria for identifying instances where the vehicle halts at a bus stop. Instances where the vehicle speed reaches zero and the door status opens at the GPS locations are isolated for further examination.

Subsequently, an extensive set of features is extracted for analysis purposes, which are categorized into two types, as detailed in Table 2. They form a vector of twenty seconds capturing time-based components indicating different aspects of driving behavior. This results in a high-dimensional feature representation that offers a comprehensive insight into driving behavior during bus stop entry. Using these feature vectors, two distinct clustering techniques, DAC and SOM, are employed.

Table 2: Features used for clustering + identifying bus stops.

Method	Feature	Unit	Type
Identifying bus stop	Door	status	
	Latitude	degrees	
	Longitude	degrees	
Clustering	Velocity	m/s	Vector of 20
	Acc. Pedal	%	Vector of 20
	Brake Pedal	%	Vector of 20
	Drivetrain Energy	kWh	Scalar
	Distance Traveled	km	Scalar

In this study, we employed the Supersom methodology to organize input variables into layers with assigned weights. Data on velocity, acceleration, and brake pedal usage were segmented into vectors representing twenty-second intervals, while distance and energy per kilometer were treated as scalars in a separate layer. The trained Supersom created a map where each maneuver was represented by a hexagon. These hexagons were then used as inputs for the K-means clustering algorithm to determine clustering results, assessing the optimal cluster number by analyzing the elbow point in the within-cluster sum of squares ($within_{ss}$) from 2 to 20 clusters. The ”kohonen” package was utilized to visualize the SOM model, presenting one layer of the codebook vectors at a time.

5 RESULTS AND DISCUSSION

5.1 Influential Factors of the Drivetrain Energy Consumption

Our research aims to comprehensively understand and analyze the factors that influence drivetrain energy consumption. To achieve this, we employ SHAP values as a powerful tool for feature attribution.

As Group 1 only differ in the initial speed of the vehicle, the influencing factors of the two scenarios only differ slightly. The two main factors influencing the drive energy are the acceleration pedal and vehicle speed (cf. Figure 3). The Figure shows the mean values of the absolute Shap values for a GPS position in the starting scenario for the respective influencing factors.The energy requirement increases with higher speeds and higher acceleration. Therefore, it is necessary to allocate more power resources to sustain acceleration and maintain the desired velocity.

As Group 2 describes situations in which the vehicle is driving, the most influencing factors for the drivetrain energy are similar to Group 1, the acceler-

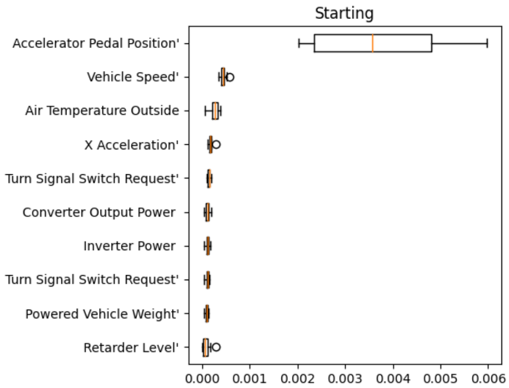

Figure 3: Top ten factors in the starting scenario.

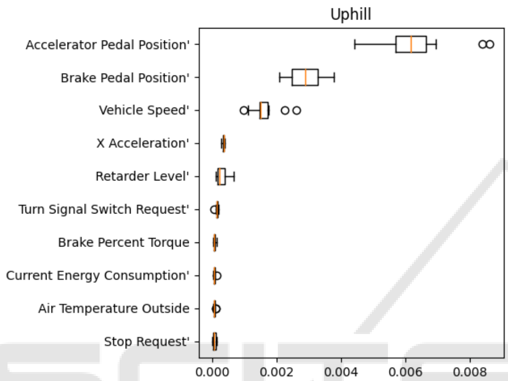

Figure 4: Top ten factors in the Uphill scenario.

ator and brake pedal position as well as the vehicle speed. These parameters can be explained physically, e.g. the increased driving resistance at higher speeds (cf. Figure 4). Firstly, the position of the accelerator pedal remains a critical determinant. The degree to which the accelerator is pressed directly impacts the amount of energy delivered to the drivetrain, influencing the vehicle's speed and acceleration.

Secondly, the brake pedal position plays a crucial role in the energy dynamics of the drivetrain. When the brake pedal is engaged, it signifies a reduction in the vehicle's speed. Conversely, releasing the brake pedal allows for the restart of the energy flow, facilitating acceleration. Thirdly, the vehicle speed emerges as another pivotal factor within this scenario group. The speed at which the vehicle is traveling is integrally linked to both the accelerator and brake pedal actions. Higher speeds generally require more energy to maintain. Besides the brake pedal, another significant factor influencing drivetrain energy consumption is the retarder, that is installed in the electrical vehicle. In addition to the primary braking mechanism provided by the brake pedal, the retarder level serves as an additional braking.

In addition to the top 10 parameters shown in Figure 3 and Figure 4, there are other parameters, that influence the drivetrain energy. The battery voltage also plays a role, since higher battery voltage results in lower energy consumption due to reduced losses from the lower currents required to meet the same power demands when compared to lower voltage situations.

The remaining range also affects the drivetrain energy, as position seven in the acceleration scenario and position 15 in the starting scenario. This may be due to the fact that drivers tend to be more aware of energy consumption when the remaining range is low. In these situations, individuals are likely to pay closer attention to their driving habits, adjusting their behavior to optimize energy efficiency as they strive to maximize the remaining distance they can cover with the available energy.

5.2 Bus Stop Based Cluster Analysis

The dataset spans January to December 2022 and includes around 45,000 instances of electric city buses arriving at stops, sourced from ten buses across cities with varying altitudes. The Analysis reveals an average speed of 20.89 km/h with a standard deviation of 9.02 km/h, showing significant speed variance. Additionally, the mean positions of the acceleration and brake pedals in the last twenty seconds reaching the bus stop were found to be 18.69% (4.07-54.92%) and 14.03% (1.57-44.21%), respectively; notably, the acceleration value of 54.92% appears to be an outlier. Instances with more than 10 seconds of missing energy consumption data at any bus stop were excluded, focusing the study on driving style and its impact on energy consumption

5.2.1 Results of DAC

In the application of the DAC model, along with K-means clustering, the data was segmented into three distinct clusters, labeled as Cluster IDs 0, 1, and 2 (cf.Figure 5). In this clustering, Cluster 2 came as the group with substantial energy consumption (Bad Cluster), as evidenced by its higher drivetrain energy metrics per kilometer (Comparison with Cluster 0: 2.024 kWh/km higher, Cluster 1: 1.481 Kwh/km higher). Conversely, Cluster 0 is recognized as a cluster with reduced energy consumption, exhibiting the least energy per kilometer with a negative value among the clusters indicating more recuperation (Good Cluster) (Comparison with Cluster 2: 2.024 kWh/km lower, Cluster 1: 0.543 Kwh/km lower). Cluster 1 displays intermediate energy consumption, higher than Cluster 0 but lower than Cluster 2 (Comparison with Cluster 0: 0.543 kWh/km higher, Cluster

2: 1.481 Kwh/km lower).

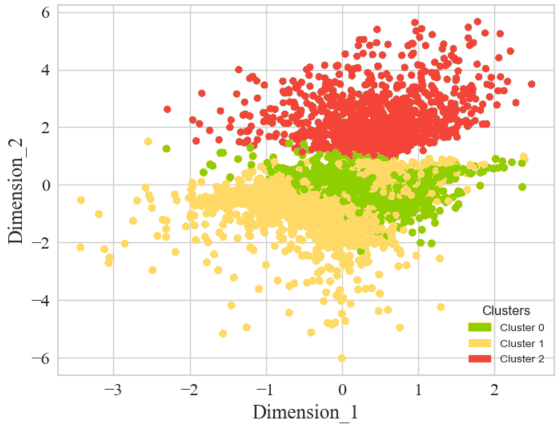

Figure 5: Three clusters resulted from the DAC and Kmeans clustering.

The high consumption cluster (Cluster 2), reveals a pattern of lesser brake pedal usage coupled with elevated acceleration values. This combination contributes to increased energy consumption and diminished energy recuperation. Vehicles in this cluster were noted to maintain lower speeds in previous time instances, necessitating increased acceleration to arrive at bus stops in a timely manner. This pattern is observable not only during times of heavy traffic but also during early morning and late-night hours in the same bus stop in different time instances, as depicted in cf.Figure 6 and indicated as the bad cluster (Cluster 2). Given that these periods typically witness reduced traffic, the driving pattern may be more reflective of individual driver behaviors or ignorance of the driver to follow energy efficient driving than external traffic conditions.

Figure 6: Driving style at early morning time period on different days at a specific bus stop.

Conversely, Cluster 0, which is characterized by the lowest energy consumption per kilometer, shows a different pattern in terms of brake and acceleration. The average brake pedal usage in this cluster is 69.75% higher than that in Cluster 2. Moreover, the acceleration observed in Cluster 0 is consistently lower compared to that in the high-consumption cluster. Ultimately, the contrast between the clusters offers insights into the diverse strategies drivers employ and their impact on energy usage.

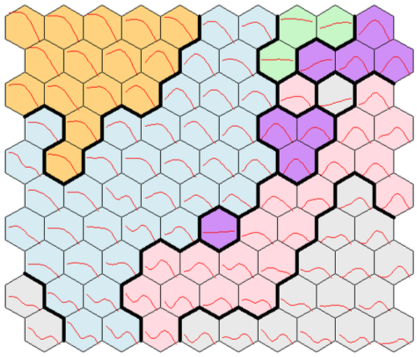

Figure 7: Code map for the vector layer **Speed (kmph)**.

5.2.2 Results of SOM

The SOM analysis was conducted using a 10x10 hexagonal grid, resulting in a total of 100 hexagons. Each hexagon in the code map corresponds to a unique node in the SOM, depicting distinct driving behaviors observed in the data. To determine the optimal clustering of these behaviors, an elbow curve analysis was utilized, which identified six as the ideal number of clusters. Therefore, the hexagons in the code map have been color-coded into six different categories, each representing a cluster. Equal weighting was assigned to all three vector layers and the singular scalar layer during the training phase of the SOM.

Upon analyzing the velocity map in cf. Figure 7, it was observed that in the orange and blue clusters, there was a gradual decrease in speed over the twenty-second time frame. In contrast, the pink and purple clusters exhibited a distinct pattern where the speed initially increased from a low point, peaked, and then decreased again, forming a trajectory similar to a half-circle as described in cf. Figure 7. The grey cluster was characterized by generally lower speed values and exhibited little variation. In the final green cluster, a consistently high speed was maintained throughout the observed period.

In the acceleration map analysis, distinct patterns emerged across the clusters (cf. Figure 8). The orange, blue, and green clusters predominantly displayed a decreasing trend in acceleration values, remaining largely within a lower range. A notable exception was identified within the blue cluster, where a peak in acceleration was observed in approximately five hexagons. In stark contrast, the pink and purple clusters exhibited a pronounced sudden peak in acceleration, which later subsided. This pattern suggests a more dynamic and variable acceleration behavior in these clusters. The grey cluster, however, presented a more nuanced pattern of acceleration, oscillating from low to high and then reverting to low, yet these fluctuations were confined to a lower range and did not exhibit the high peaks seen in the pink and purple clusters.

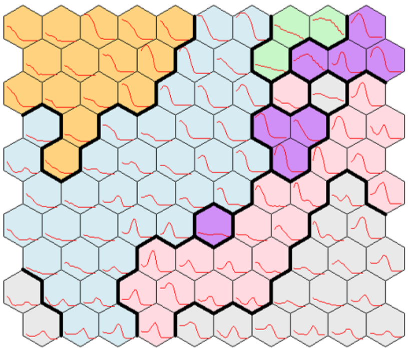

Figure 8: Code map for the vector layer **Acceleration (%)**.

In the orange and blue clusters of the brake pedal code map (cf. Figure 9), braking was applied consistently in the last twenty seconds before a bus stop, with brake values decreasing over about twelve seconds. In contrast, the pink and purple clusters showed predominant braking in the last five seconds, effective due to generally lower speeds. The grey cluster exhibited a more irregular braking pattern; in eight specific hexagons, two distinct peaks in brake value were observed, indicating variable braking behavior. Meanwhile, the green cluster showed a consistent brake value of zero, suggesting no change or application of the brakes in this cluster. These patterns highlight diverse braking strategies influenced by speed and approach to bus stops.

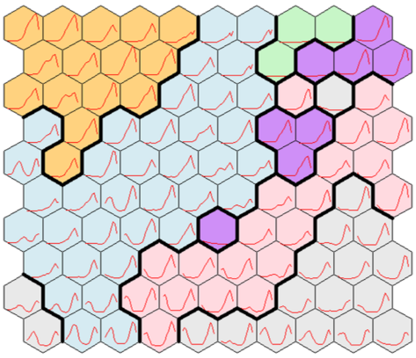

Figure 9: Code map for the vector layer **Brake pedal (%)**.

Analyzing the scalar component code map in cf. Figure 10, which details distance and energy use over twenty seconds, clear energy efficiency patterns emerged. The orange and blue clusters demonstrated greater efficiency, consuming 0.697 and 0.606 kWh/km less than the highest consumption cluster, respectively, achieving more distance (≈ 270 m) with less energy. In contrast, the purple, pink, gray, and green clusters consumed more energy (0.528, 0.426, 0.457, and 0.697 kWh/km higher, respectively) for shorter distances (≈ 120 m), indicating lower energy efficiency.

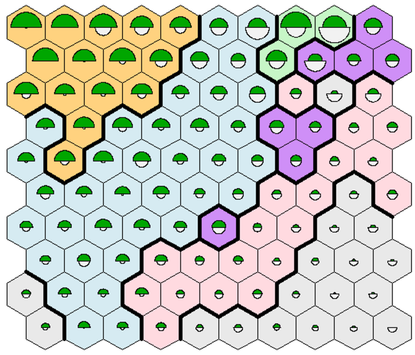

Figure 10: Code map for the scalar layer, depicting the distance traveled and energy consumed.

A count plot analysis (cf. Figure 11) of these clusters indicated a higher frequency of instances in hexagons that were less energy efficient, suggesting that certain driving styles lead to increased energy consumption during bus stop approaches. Alternatively, this pattern may also reflect a lack of awareness or concern among drivers regarding more efficient driving methods. The orange and blue clusters are characterized by a negative average energy value which is negative, indicative of effective energy recuperation as the bus approaches the stop. Within the dataset, 20,875 instances, constituting 45.86% of the total observed bus stop entries, fall into the energy-efficient clusters. Meanwhile, the clusters identified as less energy efficient comprise 24,642 instances, which equate to 54.14% of the entire set of data points.

6 CONCLUSION

In summary, this research utilizes SHAP values to comprehensively analyze drivetrain energy consumption. Two distinct scenario groups were identified: one focuses on acceleration and starting, while the other focuses on various driving conditions. Acceleration is primarily influenced by the accelerator pedal and vehicle speed, with higher speeds demanding more energy. In driving scenarios, factors such as accelerator and brake pedal positions, vehicle speed, and retarder level play crucial roles.

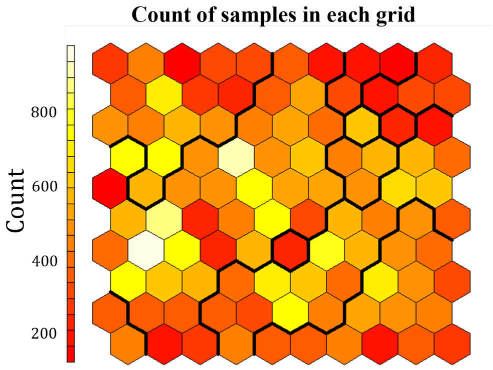

Figure 11: Number of driving instances entering the bus stop mapped into different nodes.

The DAC analysis disclosed that the cluster with elevated drivetrain energy consumption exhibited increased acceleration upon approaching bus stops, a trend which is also prevalent during early morning and nighttime periods. Likewise, the SOM analysis determined that more than half of the instances in the dataset fell into clusters characterized by energy inefficiency, thereby contributing to sub-optimal energy consumption.

By adjusting driving behaviors and reducing inefficient practices, the operational efficiency of city buses can be significantly improved. Future research could explore the nuances of energy consumption as electric city buses transition from idling to motion, particularly when departing from bus stops. This analysis would complement current findings and pave the way for the development of data-driven systems to help drivers optimize energy use during operations.

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