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MANAGING THE TRANSITION TO ELECTRIC VEHICLES

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Abstract

The shift from Internal Combustion Engine (ICE) vehicles to Electric Vehicles (EVs) is a crucial component in the United Kingdom's strategy to achieve net-zero emission by 2050. This case study centres on Southampton, a city undergoing transformation aiming to determine the optimal locations for installation of Electrical Vehicle charging station to maximise coverage while being cost efficient. To make this strategic decision combination of Operational Research (OR) techniques and Machine Learning (ML) and Artificial Intelligence (AI) were used on conversion of existing petrol stations into Electrical Vehicle (EV) charging points.

Data collection involved manually gathering datasets from Google Maps and OpenStreetMap, additionally from public and government datasets. To analyse spatial distribution for 24 existing petrol stations in Southampton, distance matrices were calculated and assessing their proximity to different districts. The study involved using clustering methods such as K-Means Clustering and Hierarchical Clustering to group stations based on their locations. To determine which station is operational or be converted to EV charging points, facility location optimisation model was developed. The aim of the model is to maximise coverage across the districts and simultaneously be cost efficient. The model's sensitivity analysis explores different distance thresholds to find most efficient strategy for the conversion. Resulting in maintaining 9 strategically positioned petrol stations, with a optimal distance of 1.5 km, providing comprehensive coverage of all the 15 districts in Southampton. This strikes balance between cost effectiveness and accessibility. Ensuring remaining Internal Combustion Engine (ICE) vehicles have adequate access to fuel simultaneously supporting the transaction to electric vehicle infrastructure. These findings suggest a practical approach to managing traditional shift from existing fuel stations to EV charging points, considering both current needs and future goals in urban transportation planning.

The research findings provide valuable insights for city planners and government officials, offering a practical approach for managing the transition to electric vehicle infrastructure in urban environments, supporting sustainability goals and aligns with national climate targets. To future enhance the model's relevance and applicability across diverse urban settings, further studies should focus on the integration of real-time data and expanding the model's scope to enhance its relevance across various urban contexts.

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1. Introduction

The transition from Internal Combustion Engine (ICE) vehicles to Electric Vehicles (EVs) is a pivotal part of the United Kingdom's strategy to achieve its net-zero emissions target by 2050. This shift is crucial, as the transport sector currently accounts for a significant proportion of the nation's greenhouse gas emissions, contributing approximately 28% of the total emissions in 2018 (Bhagavathy et al., 2020). To address this, the UK government has set ambitious goals, including banning the sale of new petrol and diesel vehicles by 2030, with the aim of ensuring that all new cars and vans are zero-emission by 2035 (Al-Wreikat and Sodré, 2023; United Kingdom Department for Transport, 2024). This transition, while necessary for environmental sustainability, poses several challenges, particularly in terms of infrastructure development, technology adoption, and socio-economic impacts.

One of the critical components of this transition is the development of a comprehensive charging infrastructure to support the growing number of EVs. Currently, there are significant disparities in the availability and distribution of charging facilities across the UK, with some regions having ample public chargers while others remain underserved (Bhagavathy et al., 2020). To address this issue, strategic placement and expansion of charging infrastructure are essential, especially in urban areas where the concentration of vehicles is high, and the potential for home charging is limited (Chen et al., 2020). In response to these needs, the UK government has implemented various policy measures, including the Zero Emission Vehicle (ZEV) mandate and financial incentives, to accelerate the adoption of EVs and promote the development of charging infrastructure (Chen et al., 2020; Al-Wreikat and Sodré, 2023). The transition also requires careful consideration of the socio-economic implications. Low-income households, rural communities, and other vulnerable groups may face significant barriers to accessing EVs and charging infrastructure due to high upfront costs, limited availability of public chargers, and a lack of targeted incentives (Ejeh, Roberts, and Brown, 2023). Addressing these disparities is essential to ensure that the benefits of EV adoption are shared equitably across different segments of society. Policies that focus on providing subsidies, expanding public charging networks, and supporting technological innovations such as Vehicle-to-Grid (V2G) technology can help bridge these gaps (Chen et al., 2020; Hu et al., 2022).

Moreover, technological advancements play a significant role in enabling a smooth transition to EVs. Innovations such as fast and wireless charging, smart grid integration, and AI-driven decision support systems can optimize the deployment and management of charging infrastructure (Yang, Zhao, and Chen, 2020; Padmanabhan et al., 2021). For instance, AI and machine learning (ML) techniques, such as reinforcement learning, can dynamically manage the placement of charging stations and adapt to changes in user demand and traffic patterns (Padmanabhan et al., 2021). These advancements not only enhance the efficiency of energy management but also reduce the need for extensive physical infrastructure (Liu, Huang, and Zhang, 2023).

This case study focuses on Southampton, a city in the UK currently navigating this transition from ICE vehicles to EVs. The goal is to determine the optimal locations for EV charging stations to maximize coverage while minimizing costs. A combination of analytical techniques, such as facility location models, clustering algorithms (K-Means and Hierarchical Clustering), and sensitivity analysis, is used to guide strategic decisions for converting existing petrol stations into EV charging points. This approach not only supports the UK's broader climate goals but also provides practical insights for local authorities and policymakers in urban areas (Chen et al., 2020; Wang et al., 2022).

2. Literature Review

2.1 Introduction for the transit from ICE to EVs

The United Kingdom is currently undertaking a substantial transition from Internal Combustion Engine (ICE) vehicles to Electrical Vehicles (EVs) as part of its broader commitment to reduce greenhouse gas emissions and achieving net-zero emissions by 2050. This transition is a critical component of the UK's climate strategy, given that the transport sector accounted for 28% of the country's total emissions in 2018 (Bhagavathy et al., 2020). The government strategy to ban all the sale of new petrol and diesel vehicles by 2030, with the aim of ensuring the transition from emission to zero-emissions by 2035 (Al-Wreikat and Sodré, 2023). This shift is not only driven by the need to decarbonize the transport sector but is also supported by advancements in battery technology, increasing consumer awareness, and a range of government incentives designed to make EVs more accessible to the public (Chen et al., 2020). However, despite these efforts, 600 million people may lack electricity by 2030, with modern renewable energy at only 12.5% of energy use in 2021. Addressing these gaps aligns with the UK's EV transaction, underscoring the need to decarbonize transport for broader sustainability goals (United Nations, 2024), (Ejeh, Roberts and Brown, 2023).

2.2 Key Strategic Decisions in the Transition to EVs

2.2.1 Infrastructure Development and policy frameworks

The development of a comprehensive charging infrastructure is a critical strategical component of the UK's transition to Electrical Vehicles (EVs). However, there is significant spatial disparity in EV uptake and charging infrastructure, with some areas, having the highest number of public chargers but allow ratio of chargers to battery electric vehicles (BEVs). This disparity underscores the need for strategic placement and expansion of infrastructure. Particularly in regions with limited access to home charging (Bhagavathy et al., 2020).

To address these challenges, the UK government has implemented various policies and regulatory frameworks in driving the adoption of EVs. Policies like the Zero Emission Vehicle (ZEV) mandate and financial incentives need to be carefully crafted to encourage the transition while also considering economic impacts, such as potential losses in fuel tax revenue (Al-Wreikat and Sodré, 2023). Financial incentives, including grants and tax benefits, have been instrumental in encouraging both private individuals and businesses to adopt EVs and invest in the necessary charging infrastructure (Chen et al., 2020).

2.2.2 Socio- Economic Impacts and Technology Adoption

In the UK, the shift to Electric Vehicles (EVs) demands meticulous planning to address socio-economic inequalities, as disadvantaged groups, including low-income households and rural residents, may encounter difficulties in accessing EVs and required charging infrastructure. Factors like income levels, geographic location, and limited government incentives contribute to uneven rates of EV adoption across the country (Bhagavathy et al., 2020; Al-Wreikat and Sodré, 2023). To reduce these disparities, policies should focus on offering targeted incentives, such as subsidies for low-income households, and expanding public charging infrastructure in areas that lack adequate access (Ejeh et al., 2023).

Technological advancements, such as fast and wireless charging, smart grid integration, and Vehicle-to-Grid (V2G) technologies, are crucial for promoting wider EV adoption and ensuring a sustainable transition (Chen et al., 2020; Hu et al., 2022). These innovations improve energy management efficiency, reduce the need for extensive physical infrastructure, and enhance grid stability by allowing EVs to return electricity to the grid during peak demand times (Chen et al., 2020; Liu et al., 2023).

2.3 Operational Research (OR) Techniques in EV Transition Planning

The transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs) involves several strategic decisions, including the optimal placement of charging infrastructure, energy distribution management, and ensuring equitable access to EVs. Operational Research (OR) techniques play a vital role in supporting decision-making in these areas by providing tools to model, solve, and address complex problems related to EV transition planning.

- **Facility Location Models**, which help determine the best sites for new EV charging stations. These models, such as covering models and P-median models, maximize accessibility for users while minimizing travel distances by considering factors like population density, traffic patterns, and proximity to existing infrastructure (Chen et al., 2020; Wang et al., 2022).

- **Multi-Criteria Decision Analysis (MCDA)** techniques, like the Analytic Hierarchy Process (AHP) and PROMETHEE, provide a structured framework for evaluating and prioritizing charging station locations based on multiple criteria such as cost, environmental impact, and social equity (Wang et al., 2022; Lima et al., 2021). These techniques help decision-makers balance various objectives and select the most appropriate sites for infrastructure development.
- **Simulation and Agent-Based Models (ABM)** are also essential for predicting infrastructure needs and user behaviour. These models simulate the behaviour of individual entities, like drivers and charging station operators, to anticipate the impact of EV adoption on infrastructure requirements over time (Shamshirband et al., 2021; Chen et al., 2021).
- **Network Optimization Models** manage electricity distribution and charging station placement to ensure the grid can handle increased loads due to widespread EV adoption, minimizing costs while maintaining stability (Yuan et al., 2020; Lee et al., 2023).

2.4 Combining OR with AI/ML Techniques for Enhanced Decision-Making

Integrating Operational Research (OR) techniques with Artificial Intelligence (AI) and Machine Learning (ML) methods offers a more dynamic and data-driven framework for strategic decision-making in the transition to electric vehicles (EVs). OR techniques, such as facility location models and multi-criteria decision analysis (MCDA), provide systematic methods for optimizing the placement of charging stations and allocating resources effectively. However, AI and ML enhance these traditional OR approaches by introducing real-time adaptability and predictive capabilities.

Reinforcement Learning (RL), an AI technique, allows for dynamic adjustment of charging station placement based on real-time data and evolving demand patterns. For example, Deep Q-Networks (DQN), a form of RL, have demonstrated significant improvements in infrastructure efficiency by predicting high-demand locations and adapting to changes in user behaviour (Padmanabhan et al., 2021). This integration enables planners to move beyond static models, making infrastructure placement more responsive to actual conditions and user needs (Sadeghi-Barzani et al., 2020).

Furthermore, integrating OR and AI/ML methods within a Decision Support System (DSS) enhances the overall planning process by combining long-term optimization with short-term adaptability. AI-driven models can continuously learn from new data, refining decision-making processes and ensuring infrastructure development remains aligned with evolving demand patterns and grid capabilities (Zhang et al., 2021; Liu et al., 2023). This holistic approach facilitates a balanced strategy that optimizes infrastructure development, cost management, and service delivery.

2.5 Literature Gap

This literature review demonstrates the critical role of combining Operational Research (OR) techniques with Artificial Intelligence (AI) and Machine Learning (ML) in enhancing strategic decision-making for the transition to electric vehicles (EVs). The application of facility location models, multi-criteria decision analysis (MCDA), and simulation models helps optimize infrastructure placement, manage grid loads, and address socio-economic disparities (Chen et al., 2020; Wang et al., 2022). Integrating AI/ML techniques, such as reinforcement learning, further improves responsiveness to real-time demand changes, promoting a dynamic and adaptive planning approach (Padmanabhan et al., 2021). The insights from the City of Southampton case study validate these methods by providing practical examples of how they can be tailored to local contexts, emphasizing the importance of a comprehensive and data-driven strategy for achieving an equitable and sustainable EV transition.

3 Methodology

3.1 Data Collection

To support the analysis of the transition a comprehensive dataset was compiled, focusing on the geographical distribution, vehicle count, and datasets of petrol stations in the region. Data were collected manually and supplemented with publicly available information from a variety of sources.

- **Petrol Station Data:** Data on 24 petrol stations in Southampton, including their locations (latitude and longitude), station names, addresses, operating hours, and the number of pumps, were manually collected using Google Maps and OpenStreetMap (OSM).

  The data collected included the following columns:

  a. **Station_ID**: Represents the postcode of the fuel station, serving as a unique identifier for each station.
  b. **Station_Name**: The name of the petrol station.
  c. **Address**: The full address of the petrol station.
  d. **Station_Latitude** and **Station_Longitude**: The geographical coordinates of each station, used for distance calculations and clustering analysis.
  e. **Open_24/7**: Indicates whether the station operates 24 hours a day, 7 days a week.
  f. **ICE_Vehicle_Count**: The estimated number of ICE vehicles served by each station.
  g. **Number_of_Pumps**: The total number of fuel pumps available at each station.

  This data provided a reliable foundation for the subsequent analysis, allowing for accurate modelling of the geographical distribution and operational characteristics of the stations.

- **Estimating ICE Vehicle Counts:** The estimated number of ICE vehicles served by each petrol station was derived using a coverage ratio formula. The formula calculates the proportion of ICE vehicles covered by each station relative to the total number of ICE vehicles within a district. This approach allowed for a standardized estimation of vehicle coverage across different districts in Southampton:

$$ICE\ Vehicle\ Count(Coverage\ ratio) = \frac{Number\ of\ Cover\ ICE\ Vehicles}{Total\ ICE\ Vehicles\ in\ the\ District}$$

This formula provided an estimation of how many ICE vehicles each station could potentially serve, which was crucial for understanding demand patterns and optimizing the placement of EV charging stations.

- **Supplementary Data Sources**:

  a. Information on the geographical boundaries and coordinates for different districts within Southampton was obtained from the *Postcodes in Southampton Unitary Authority* dataset (Postcodes in Southampton Unitary Authority, 2024).
  b. The *Vehicle Licensing Statistics Data Tables* provided insights into vehicle distribution and density across various postcodes in Southampton, which helped assess the demand for petrol stations and future EV charging infrastructure (Department for Transport, 2024).

3.2 Distance Matrix Computation

To analyse the geographical distribution of petrol stations in Southampton and their proximity to district postcodes, two distance matrices were constructed: a **Station_to_District** Distance Matrix and a **Station_to_Station** Distance Matrix. These matrices are essential for understanding which petrol stations are optimally located for conversion to electric vehicle (EV) charging stations and which ones could be considered for closure.

- **Station-to-District Distance Matrix**:

This matrix captures the distance between each petrol station and every district in Southampton. The geographical coordinates (latitude and longitude) of both the petrol stations and the district centres were used to calculate these distances. The **geodesic distance** formula, which measures the shortest path between 2 points on the Earth's surface, was applied to compute the distance between each petrol station and district centre. The Python **geopy** library's **geodesic** method was employed to perform these calculations, as it provides accurate distances over the curved surface of the Earth (Geopy, 2024).

The resulting matrix serves as a foundation for understanding how accessible each petrol station is to different parts of Southampton. This is particularly relevant for planning the locations of EV charging stations, where strategic placement is key to ensuring broad coverage and ease of access for all residents.

- **Station-to-Station Distance Matrix**:

In addition to calculating the distances between petrol stations and districts, a matrix was created to measure the distance between each pair of petrol stations. This matrix helps identify clusters of petrol stations that are close to one another and could potentially be consolidated or strategically converted into EV charging stations. The same geodesic method was applied to compute these distances.

Formula:
The distance between 2 points on the Earth's surface was calculated using the geodesic distance formula:

$$\boldsymbol{Distance} = \boldsymbol{Geodesic}((\boldsymbol{Latitude_1}, \boldsymbol{Longitude_1}), (\boldsymbol{Latitude_2}, \boldsymbol{Longitude_2}))$$

Where:
- $(Latitude_1, Longitude_1)$ are the coordinates of a petrol station, and
- $(Latitude_2, Longitude_2)$ are the coordinates of either a district center or another petrol station.

The geodesic distances were calculated iteratively for all station-district and station-station combinations. This allowed for a comprehensive understanding of how the petrol stations are distributed geographically and their relative proximity to various districts in Southampton. Figure.1 Shows the Python Code Snippet for Distance Calculation.

```python
from geopy.distance import geodesic

# Calculate distances from each station to each district
for i, station in stations.iterrows():
    for j, district in districts.iterrows():
        coord_station = (station['Station_Latitude'], station['Station_Longitude'])
        coord_district = (district['District_Latitude'], district['District_Longitude'])
        distance = geodesic(coord_station, coord_district).km
        station_to_district_matrix.loc[station['Station_ID'], district['Postcode']] = distance
```

Figure. 1 Code Snippet for Distance Calculation

3.3 Normalization of Distance Matrices:

To ensure the distance values were on a comparable scale for clustering analysis, both the Station-to-District and Station-to-Station Distance Matrices were normalized. Normalization involved adjusting the values so that they had a mean of 0 and a standard deviation of 1, making them suitable for clustering algorithms that are sensitive to the scale of input data (Scikit-learn, 2024). Figure. 2 Shows the code Normalization of Distance Matrix using **StandardScaler** method.

```python
from sklearn.preprocessing import StandardScaler

# Normalize the station-to-district and station-to-station matrices
scaler = StandardScaler()
normalized_station_to_district = scaler.fit_transform(station_to_district_matrix.fillna(0))
normalized_station_to_station = scaler.fit_transform(station_to_station_matrix.fillna(0))
```

Figure. 2 code Normalization of Distance Matrix using **StandardScaler** method.

3.4 Clustering Techniques:

To understand the geographical distribution of petrol stations and optimize their management during the transition to electric vehicle (EV) charging stations, two clustering techniques were employed: **K-Means Clustering** and **Hierarchical Clustering**. These techniques grouped petrol stations based on their proximity to districts and to each other, providing insights for strategic decisions on which stations to convert or close.

3.4.1 K-Means Clustering:

The K-Means clustering technique was applied to the normalized station-to-district distance matrix to group petrol stations based on their distances from various districts. K-Means is a method that divides the data into a predefined number of clusters, aiming to minimize the variance within each cluster.

To determine the optimal number of clusters, the **Elbow Method** was used. The Elbow Method involves in plotting the sum of squared distances (inertia) between each point and the centroid of its assigned cluster against different numbers of clusters. The optimal number is chosen at the point a where the inertia begins to decrease less sharply, forming an "elbow." Figure. 3 Shows the Elbow Curve, the optimal number of clusters was determined to be 3.

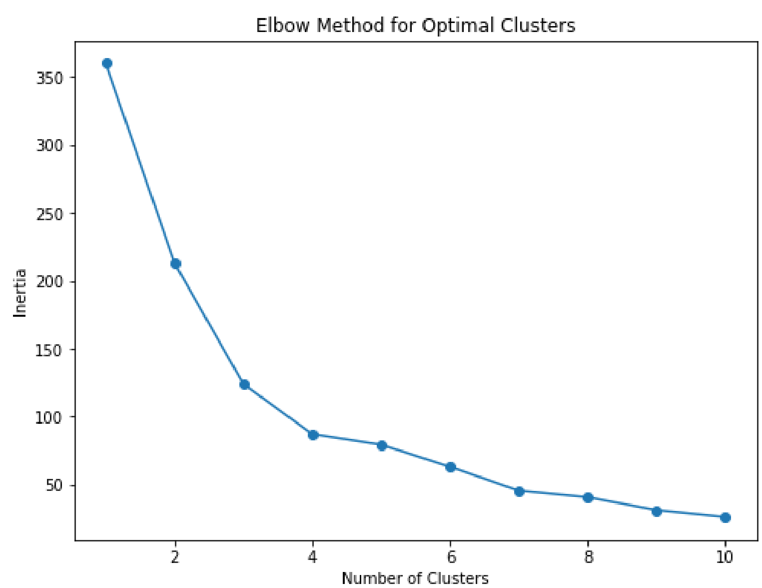

Figure. 3 Elbow Cure for K-Means Clustering

After determining the optimal number of clusters, K-Means clustering was applied, resulting in three distinct groups of petrol stations (clusters 0, 1, and 2). Figure 4 illustrates the clustering of petrol stations based on their distances to various districts and Figure. 5 Shows the code for K-Means Clustering.

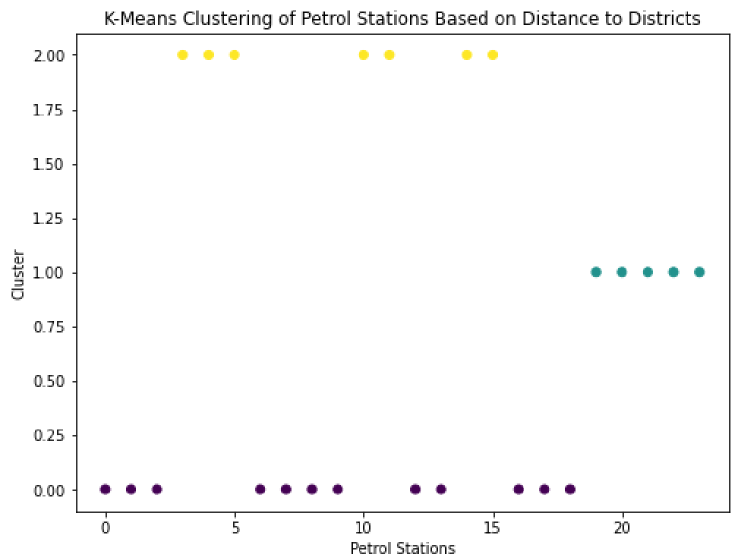

Figure. 4 illustrates the clustering of petrol stations based on their distances to various districts

K-Means Clustering identified three distinct groups of petrol stations, suggesting which stations were geographically well-positioned to serve multiple districts and which might be most suitable for conversion to EV charging stations to maximize coverage.

```python
## K-Means Clustering

# Define the number of clusters
n_clusters = 3  # This can be set based on the elbow method result

# Apply K-Means Clustering on normalized station-to-district matrix
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
station_to_district_matrix['Cluster'] = kmeans.fit_predict(normalized_station_to_district)

# Visualize the Clusters
plt.figure(figsize=(8, 6))
plt.scatter(range(len(station_to_district_matrix)), station_to_district_matrix['Cluster'], c=station_to_district_matrix['Cluster'], cmap='viridis')
plt.xlabel('Petrol Stations')
plt.ylabel('Cluster')
plt.title('K-Means Clustering of Petrol Stations Based on Distance to Districts')
plt.show()

print("K-Means Clustering Results for Stations-to-Districts:")
print(station_to_district_matrix[['Cluster']])
```

Figure. 5 Code for K-Means Clustering

3.4.2 Hierarchical Clustering:

Hierarchical clustering was used as a complementary technique to understand the hierarchical relationships among petrol stations. Unlike K-Means, hierarchical clustering does not require specifying the number of clusters beforehand. Instead, it creates a dendrogram (tree diagram) that visually represents the nested clustering structure, providing a more flexible analysis.

The Ward method was chosen for hierarchical clustering, as it minimizes the variance within each cluster. This method was applied to the normalized station-to-station distance matrix, generating the dendrogram shown in Figure 6.

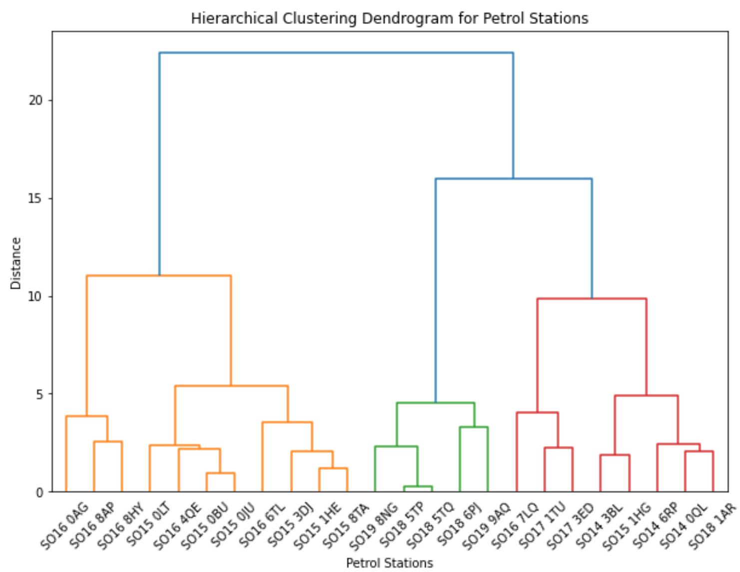

Figure. 6 Hierarchical Clustering Dendrogram for Petrol Stations

The dendrogram illustrates the hierarchical grouping of petrol stations based on their proximity to one another. By analysing the tree structure, several natural groupings of stations were identified, providing insights into potential consolidations or closures while maintaining sufficient coverage across the city. Figure. 7 Shows the Code for Hierarchical clustering.

```
from scipy.cluster.hierarchy import linkage, dendrogram

# Perform hierarchical clustering using the Ward method on station-to-station distance matrix
Z = linkage(normalized_station_to_station, method='ward')

# Plot the dendrogram
plt.figure(figsize=(10, 7))
dendrogram(Z, labels=station_to_station_matrix.index)
plt.title('Hierarchical Clustering Dendrogram for Petrol Stations')
plt.xlabel('Petrol Stations')
plt.ylabel('Distance')
plt.show()
```

Figure. 7 Code for Hierarchical clustering.

3.5 Visualization of Clusters:

To better understand the geographical distribution and relationships among the clustered petrol stations, a visualization was created using a mapping tool. This visualization helps identify potential stations for conversion to electric vehicle (EV) charging stations and provides insights into which stations could be closed or consolidated while still maintaining sufficient coverage across the city of Southampton.

3.5.1 Visualization Method:

An interactive map was created using **Folium**, a Python library for mapping that enables the visualization of geospatial data (Folium, 2024). The map displayed all 24 petrol stations in Southampton and highlighted their assigned clusters (0, 1, or 2) from the K-Means clustering analysis. This approach allowed for a clear understanding of how stations are geographically grouped. Figure. 8 Shows the Interactive Map of geospatial data.

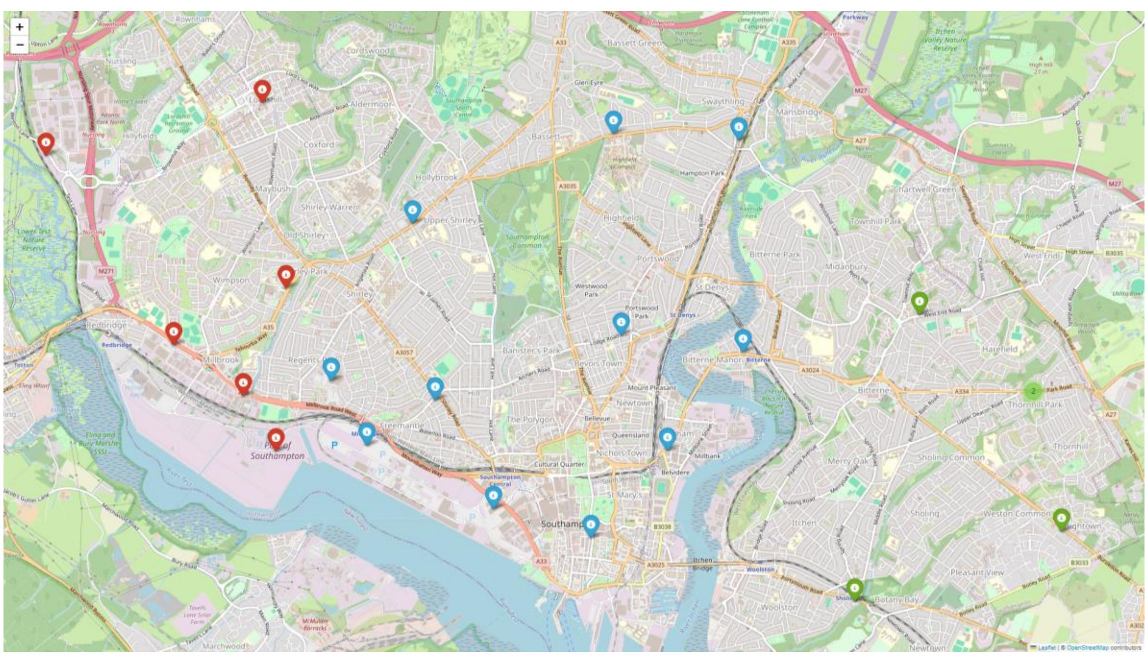

Figure. 8 Interactive Map of Geospatial data.

Different colours were used to represent each of the three clusters identified by the K-Means analysis:

- **Cluster 0:** Represented by blue markers.
- **Cluster 1:** Represented by green markers.
- **Cluster 2:** Represented by red markers.

This colour coding visually distinguished the clusters on the map, making it easier to interpret the spatial distribution of the stations. Stations that did not belong to any specific cluster due to missing data were marked in black.

The visualization in Figure. 8 revealed the spatial distribution of the petrol stations across Southampton and how they grouped into three clusters. The map made it clear which stations were located near multiple districts and could be strategic points for EV charging stations, while others were more isolated and potentially suitable for closure.

3.6 Facility Location Optimization Model:

To strategically manage the transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs), a facility location optimization model was developed. This model aimed to identify which petrol stations should remain open or be converted to EV charging stations to maximize coverage while considering the constraints of distance and the total number of stations that can remain operational.

- **Objective**:

  The objective of the optimization model was to maximize the number of districts covered by at least one open petrol station within a specified distance threshold ($\boldsymbol{x}$ kilometres). This ensures that the remaining ICE vehicles have adequate access to refuelling stations while facilitating a gradual transition to EV infrastructure (Yang, Zhao & Chen, 2020).

- **Decision Variables:**

  The model defined two sets of binary decision variables:

  1. $\boldsymbol{y_i} \in \{\mathbf{0}, \mathbf{1}\}$ **:** Binary variable Indicates whether petrol station **i** is open (1) or closed (0).

i = 1, 2, ... *N* (Where ***N*** is the total number of petrol station)

2. $\boldsymbol{z_j} \in \{\mathbf{0}, \mathbf{1}\}$ Indicates whether district **j** is covered by at least one open station within the specified distance $\boldsymbol{x}$ (1 if covered, 0 if not).

   j = **1, 2, ... *M*** (Where ***M*** is the total number of postcodes)

- **Constraints:**

1. **Coverage Constraint:** Each postcode **j** should be covered by at least one open petrol station **i** within distance $\boldsymbol{x}$:

$$\sum_{\substack{i=1 \\ d_{ij} \leq x}}^{N} y_i \geq z_j, \forall_j = 1, 2, \dots M$$

Where:

- $\boldsymbol{d_{ij}}$ is the distance between petrol station $\boldsymbol{i}$ and postcode $\boldsymbol{j}$**.**
- $\boldsymbol{x}$ is the distance threshold

2. **Station Limitation Constraint:** No more than 40% of the total petrol stations should remain open:

$$\sum_{i=1}^{N} y_i \leq 0.4\, N$$

Where:

- $\boldsymbol{y_i}$ is the binary Variable Indicates whether petrol station **i** is open (1) or closed (0).

3. **Clustering Constraint:** At least one petrol station must remain open in each cluster $\boldsymbol{k}$:

$$\sum_{i \in C_k} y_i \geq 1, \forall_k = 1, 2, \dots K$$

Where:

- $\boldsymbol{C_k}$ is the set of petrol stations in cluster $\boldsymbol{k}$.
- $\boldsymbol{K}$ is the total number of clusters.

The optimization model was implemented in Python using the **PuLP** library, which allows for the formulation and solving of linear programming problems (PuLP, 2024).

3.7 Sensitivity Analysis:

To evaluate the robustness and effectiveness of the facility location optimization model, a sensitivity analysis was conducted. Sensitivity analysis is crucial in understanding how variations in key parameters, such as the distance threshold ($\boldsymbol{x}$), affect the model's outputs. This ensures that the proposed solution is adaptable to different scenarios and uncertainties (Liu, Huang & Zhang, 2023).

- **Objective of Sensitivity Analysis**:
  The objective was to determine how varying the distance threshold ($\boldsymbol{x}$) between petrol stations and districts impacts the number of covered districts, the status of stations (open or closed), and the overall coverage percentage. By examining these changes, the analysis aimed to identify the optimal distance threshold that maximizes district coverage while minimizing the number of stations required to remain open.

- **Procedure for Sensitivity Analysis**:
  The distance threshold ($\boldsymbol{x}$) was varied from **0.5 km to 3.0 km** in increments of **0.5 km**. For each value of $\boldsymbol{x}$, the optimization model was solved to determine the number of covered districts, the status of each petrol station (open or closed), and the coverage percentage. The range of $\boldsymbol{x}$ was chosen to reflect realistic variations in the accessibility of petrol stations within the urban area of Southampton. The results were recorded, and the impact of different values of $\boldsymbol{x}$ on the model's outputs was analysed to identify trends and patterns.

4 Results and Analysis

4.1 Optimization Results:

The results showed that with a smaller value of $\boldsymbol{x}$, fewer districts were covered, whereas increasing $\boldsymbol{x}$ led to a higher coverage percentage but also required more stations to remain open. This trade-off informed the decision-making process for selecting the optimal stations to remain open or be converted (Sadeghi-Barzani, Rajabi-Ghahnavieh & Kazemi-Karegar, 2020).

4.2 Results of Sensitivity Analysis:

A sensitivity analysis shows that by varying the distance threshold ($\boldsymbol{x}$) from 1.0 km to 5.0 km in increments of 0.5 km. This helped determine how different values of $\boldsymbol{x}$ affect the number of open stations, covered districts, and overall coverage percentage. The analysis ensured that the proposed solution was robust and adaptable to different scenarios and uncertainties (Liu, Huang & Zhang, 2023). The results of the sensitivity analysis are summarized in the Figure. 9:

Optimization Results for Different x Values:

x_value	number_of_districts_covered	optimal_solution_percentage
0.5	7	46.666667
1.0	11	73.333333
1.5	15	100.000000
2.0	15	100.000000
2.5	15	100.000000
3.0	15	100.000000

Figure. 9 Sensitivity Analysis Results

- At $\boldsymbol{x}$ =**0.5 km**, only **7** districts were covered, resulting in a coverage percentage of **46.67%.**
- At $\boldsymbol{x}$ =**1.0 km**, the number of covered districts increased to **11**, with a coverage percentage of **73.33%.**
- At $\boldsymbol{x}$ =**1.5 km**, all **15** districts were covered, achieving a coverage percentage of **100%**.
- Increasing the distance threshold further to **2.0 km, 2.5 km, and 3.0 km** continued to cover all **15** districts, maintaining the **100%** coverage rate. However, these higher values did not

provide additional coverage benefits and could potentially require more stations to remain open, which may increase operational costs.

- **Optimal Distance Threshold:** Based on the sensitivity analysis, the optimal distance threshold was determined to be $\boldsymbol{x}$ **=1.5 km**. At this distance, all **15** districts were covered, and the solution was both feasible and efficient, ensuring the maximum coverage with the minimal necessary number of open stations.

- **Detailed Results** for $\boldsymbol{x}$ **=1.5 km:** Figure. 10 Shows the detailed results of the sensitivity analysis for $\boldsymbol{x}$ = 1.5 km.

Results for x = 1.5 km:

Station ID	Name	Districts Covered	Status
SO15 3DJ	BP	3	Open
SO18 6PJ	Esso	2	Close
SO16 4QE	Tesco	2	Close
SO14 3BL	Texaco	1	Close
SO16 0AG	Watson Fuels	0	Close
SO15 8TA	Costco	3	Close
SO16 8HY	Shell	1	Close
SO18 5TQ	Esso	2	Close
SO16 8AP	BP	1	Open
SO15 0JU	Asda Express	2	Close
SO14 6RP	Tesco	2	Close
SO14 0QL	Esso	1	Open
SO18 1AR	Manor	0	Close
SO15 1HE	Certas Energy	1	Close
SO19 9AQ	BP	2	Open
SO15 0LT	Shell	2	Open
SO15 1HG	Commercial Fuel Solutions Ltd	3	Close
SO16 6TL	Shell	1	Close
SO17 3ED	Shell	2	Open
SO19 8NG	BP	2	Close
SO15 0BU	AS 24	0	Close
SO17 1TU	Shell	3	Open
SO18 5TP	Morrison's	3	Open
SO16 7LQ	Shell	1	Close

Figure. 10 Sensitivity Analysis Results for $\boldsymbol{x}$ **= 1.5 km**

At $\boldsymbol{x}$ **=1.5 km**, the model determined that **9 petrol stations should remain open** to achieve full coverage of all districts, while the remaining **15 stations could be closed**. This configuration was deemed the most efficient solution, balancing operational costs and accessibility. At $\boldsymbol{x}$ **=1.5 km** distance, full district coverage was achieved with a feasible and efficient allocation of resources.

The analysis also highlighted the importance of selecting an appropriate distance threshold to balance coverage needs with the goal of minimizing the number of open stations, thereby optimizing costs and infrastructure use.

5 Discussion and Implications

The results of the facility location optimization model and sensitivity analysis provide several important insights into the strategic management of petrol stations during the transition to electric vehicles (EVs). The following discussion highlights the key findings and their implications for decision-makers in Southampton.

5.1 Implications for Decision-Making

- **Efficient Resource Allocation:** The study provides a framework for optimising resource allocation by determining which stations to be converted to EV charging hubs and which to close. This approach ensures a cost-effective transition while maintaining essential services for remaining ICE vehicles.

- **Guidance for Local Authorities:** The results offer practical guidance for local authorities in Southampton and other urban areas. By implementing the proposed strategy, local governments can achieve a smoother transition to EV infrastructure, reduce redundancy in the existing petrol station network, and align with national goals to phase out ICE vehicles by 2030 (UK Department for Transport, 2024).

- **Support for Sustainable Development Goals:** The optimized strategy supports the United Kingdom's Sustainable Development, which aims to ensure access to affordable, reliable, sustainable, and modern energy for all. The findings contribute to this goal by promoting the efficient deployment of EV infrastructure in urban areas (Goal 7, Department of Economic and Social Affairs, 2024).

- **Guiding the Transition to EV Infrastructure:** The findings provide a clear strategy for transitioning from ICE to EV infrastructure in Southampton. By maintaining a small number of strategically located petrol stations, the city can continue to support ICE vehicles during the transition period while gradually converting selected stations to EV charging hubs. This approach minimizes redundancy, reduces costs, and ensures that EV infrastructure is accessible and well-integrated into the existing transportation network (Yang, Zhao & Chen, 2020).

- **Infrastructure Planning and Investment:** The analysis also has implications for infrastructure planning and investment decisions. By understanding which stations are most critical to maintaining coverage, planners can prioritize investments in converting these stations to EV charging infrastructure. Additionally, the identification of stations that can be closed without significantly impacting coverage allows for better allocation of resources and investment towards more sustainable energy solutions (Chen et al., 2020).

6 Conclusion

The transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs) represents a critical step in achieving environmental sustainability and aligning with national and global climate goals. This case study focused on optimizing the management of petrol stations in Southampton during this transition by developing a facility location optimization model and conducting a sensitivity analysis.

- The facility location optimization model identified that maintaining 9 strategically located petrol stations would provide full coverage of all 15 districts in Southampton at an optimal distance threshold of 1.5 km, and achieving a 100% coverage rate. This result indicates that a moderate distance threshold is sufficient to ensure accessibility for remaining internal combustion engine (ICE) vehicles while minimizing the number of operational petrol stations. This finding is consistent with the objectives of balancing cost efficiency and service accessibility (Liu, Huang & Zhang, 2023).

- The sensitivity analysis demonstrated that increasing the distance threshold beyond 1.5 km did not yield additional coverage benefits, suggesting that this threshold represents the most efficient balance between coverage and the number of open stations. Lower thresholds resulted in reduced coverage, while higher thresholds maintained full coverage but potentially increased operational costs. The chosen threshold of 1.5 km represents a balanced solution, offering full coverage while keeping the number of open stations manageable (Sadeghi-Barzani, Rajabi-Ghahnavieh & Kazemi-Karegar, 2020).

- The study's findings highlight the importance of using data-driven decision-making tools, such as optimization models and clustering techniques, to guide strategic decisions in managing the transition to EVs. By identifying the optimal distance threshold and strategically selecting stations to remain open or be converted, policymakers can minimize costs while ensuring accessibility and service continuity. This strategy aligns with the goal of gradually transitioning to EV infrastructure while maintaining essential services for ICE vehicles.

The shift towards electric vehicles (EVs) constitutes a crucial element of international initiatives aimed at alleviating climate change and diminishing carbon emissions. By leveraging the data-driven approaches such as the facility location optimisation model used in this study, cities like Southampton can make informed decisions that balance cost, accessibility, and sustainability. The findings in this study provide a roadmap for effective management of the transition to EV infrastructure and underscore the importance of continued research and collaboration among policymakers, businesses, and the community.

7 Future Enhancements

- **Integration of Real-Time Data:** Future research can be involved incorporate the real-time data on traffic patterns, vehicle usage, and energy demand to refine the optimisation model. This would enhance its adaptability to dynamic urban environments and changing transportation needs (Liu, Huang & Zhang, 2023).

- **Consideration of Additional Factors:** Additional factors, such as social equity, public transportation integration, and renewable energy sourcing, could be considered in future models to provide more comprehensive approach to urban transportation planning (Chen et al., 2020).

- **Broader Geographic Scope:** Expanding the model to include a broader geographic scope beyond Southampton could provide insights into regional or national strategies for managing the transition to EVs. Comparative studies across different urban areas could identify best practices and common challenges in deploying EV infrastructure (Al-Wreikat and Sodré, 2023).

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