In [ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [ ]:
```python
# Load data
data = pd.read_csv('Data.csv')
X = data.drop(['Health_State_of_Meter'], axis=1)
X.head()
```

Out[ ]:

	Profile_Factor	Symmetry	Crossflow	Flow_Velocity1	Flow_Velocity2	Flow_Velocity3	Flow_Velocity4
0	1.10	1.00	0.99	2.35	2.60	2.58	2.35
1	1.09	1.00	1.00	3.40	3.71	3.71	3.41
2	1.08	1.01	1.00	3.44	3.71	3.69	3.42
3	1.09	1.01	0.99	3.40	3.73	3.66	3.37
4	1.09	1.01	1.00	3.40	3.70	3.68	3.35

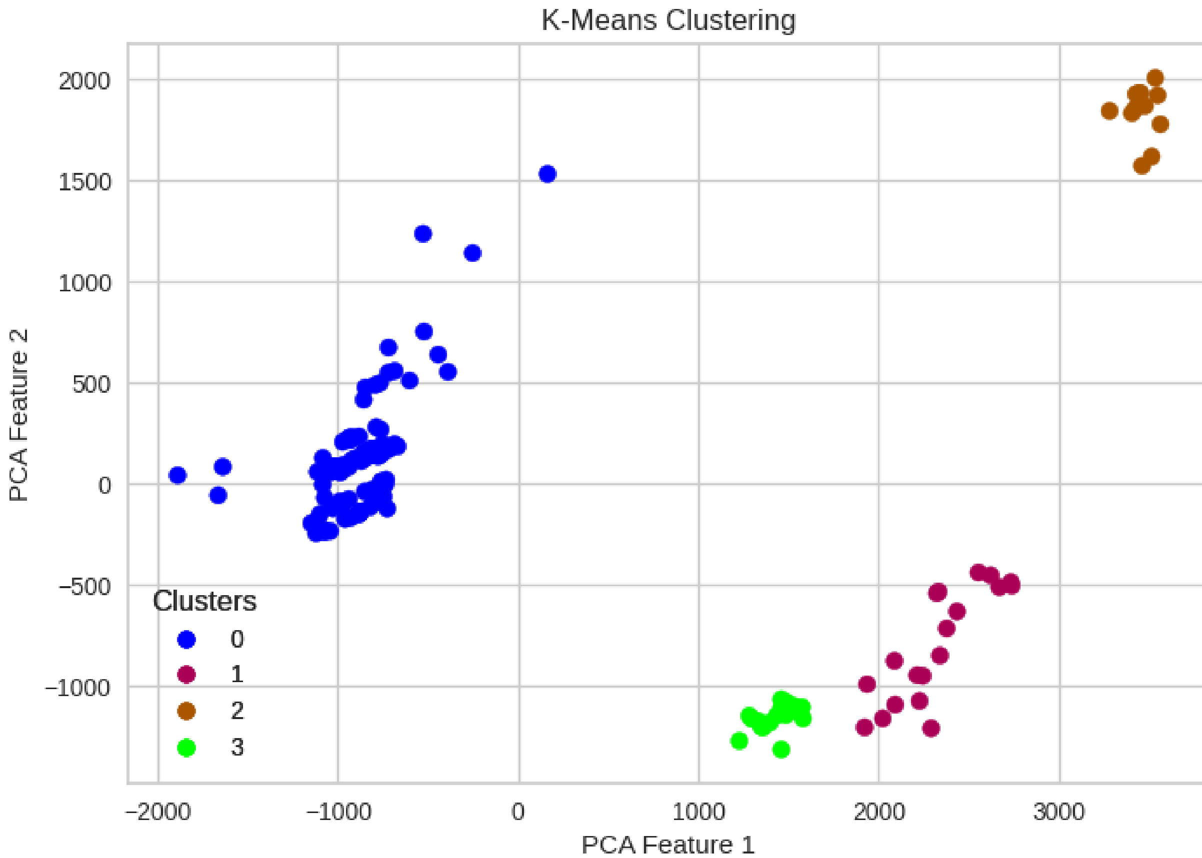
5 rows × 43 columns

In [ ]:
```python
#PCA

from sklearn.decomposition import PCA
pca_2 = PCA(n_components=2)
X_pca = pca_2.fit_transform(X)
```

In [ ]:
```python
#Visualizing the clusters
def plot_clusters(X, labels, title):
  fig, ax = plt.subplots()
  scatter = ax.scatter(X_pca[:, 0], X_pca[:, 1], c=labels, cmap='brg', s=50)
  ax.set_title(title)
  ax.set_xlabel('PCA Feature 1')
  ax.set_ylabel('PCA Feature 2')
  legend = ax.legend(*scatter.legend_elements(), loc="lower left", title="Clusters")
  ax.add_artist(legend)
  plt.show()
```

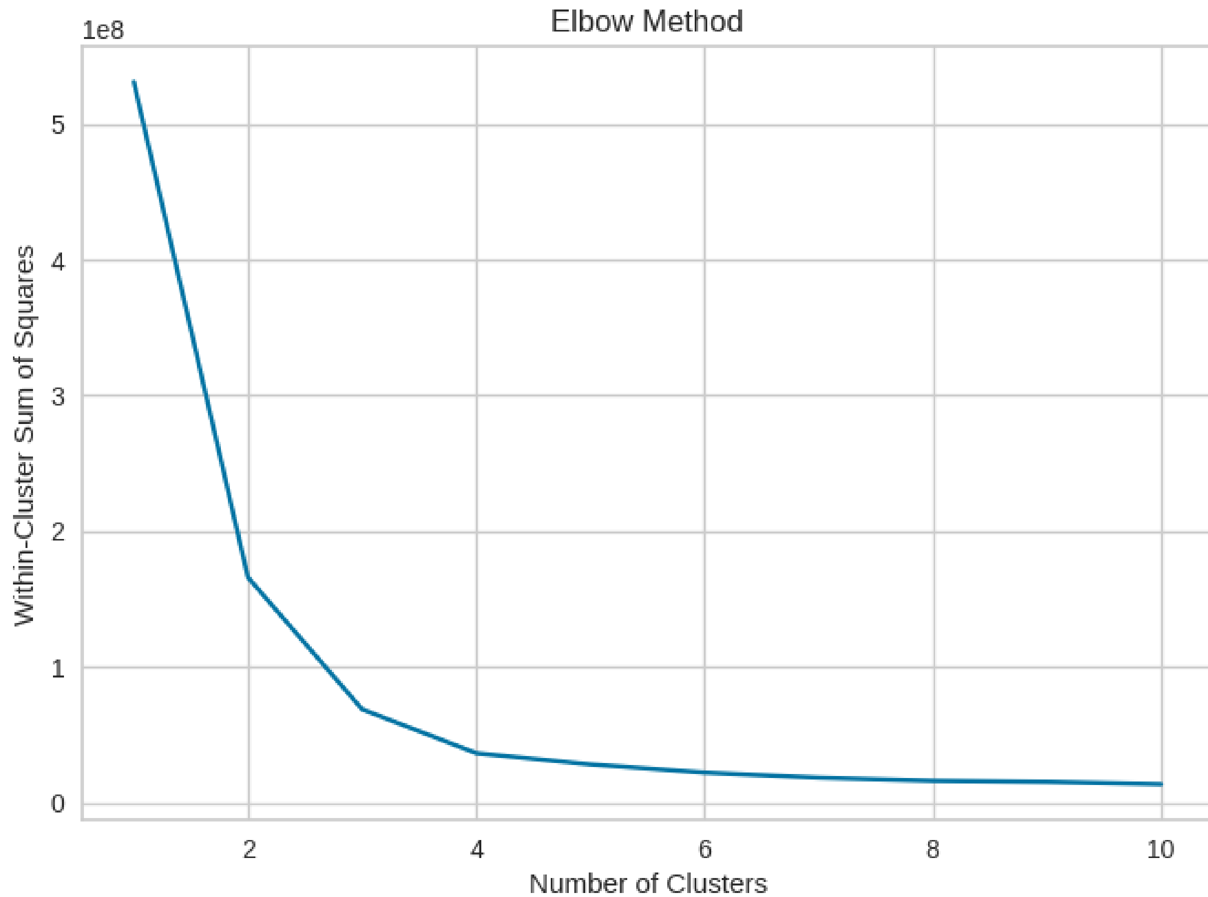
K Means Clustering

In [ ]:
```python
from sklearn.cluster import KMeans

# Perform k-means clustering
kmeans = KMeans(n_clusters=4, random_state=0).fit(X)
labels = kmeans.labels_

plot_clusters(X_pca, labels, 'K-Means Clustering')
```



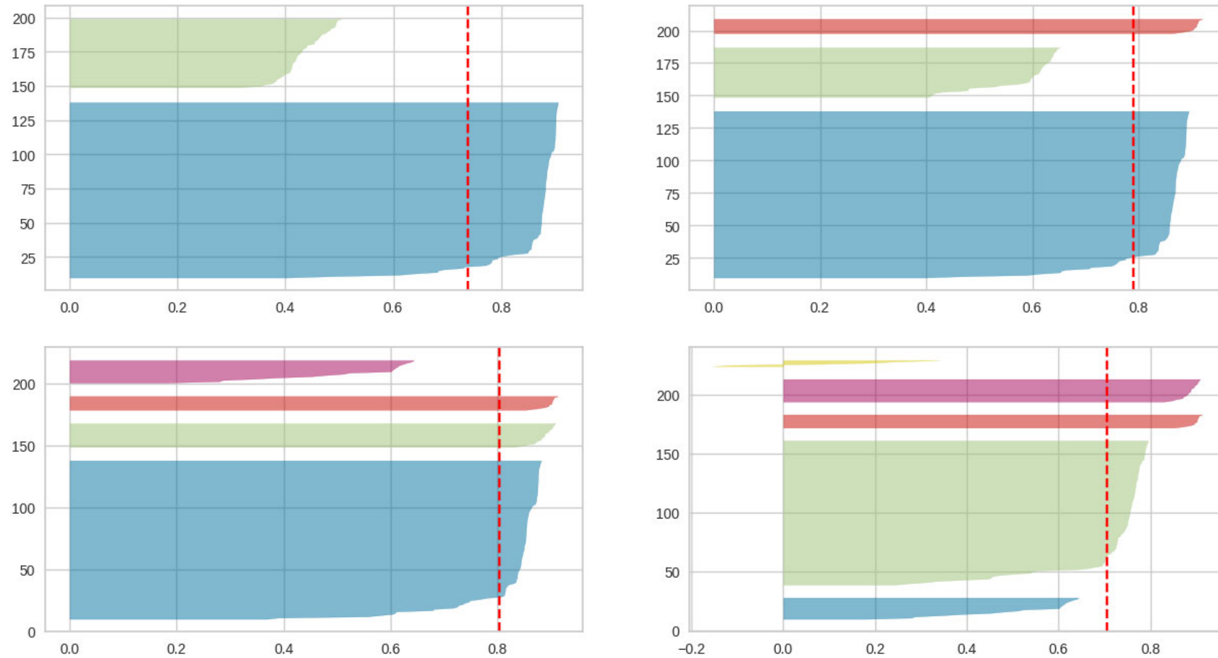
In [ ]:

```
# Perform elbow method to determine optimal number of clusters
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=0, n_init=10).fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('Within-Cluster Sum of Squares')
plt.show()
```



It is not clear where the elbow joint lies, it is either for number of clusters being either 3 or 4.

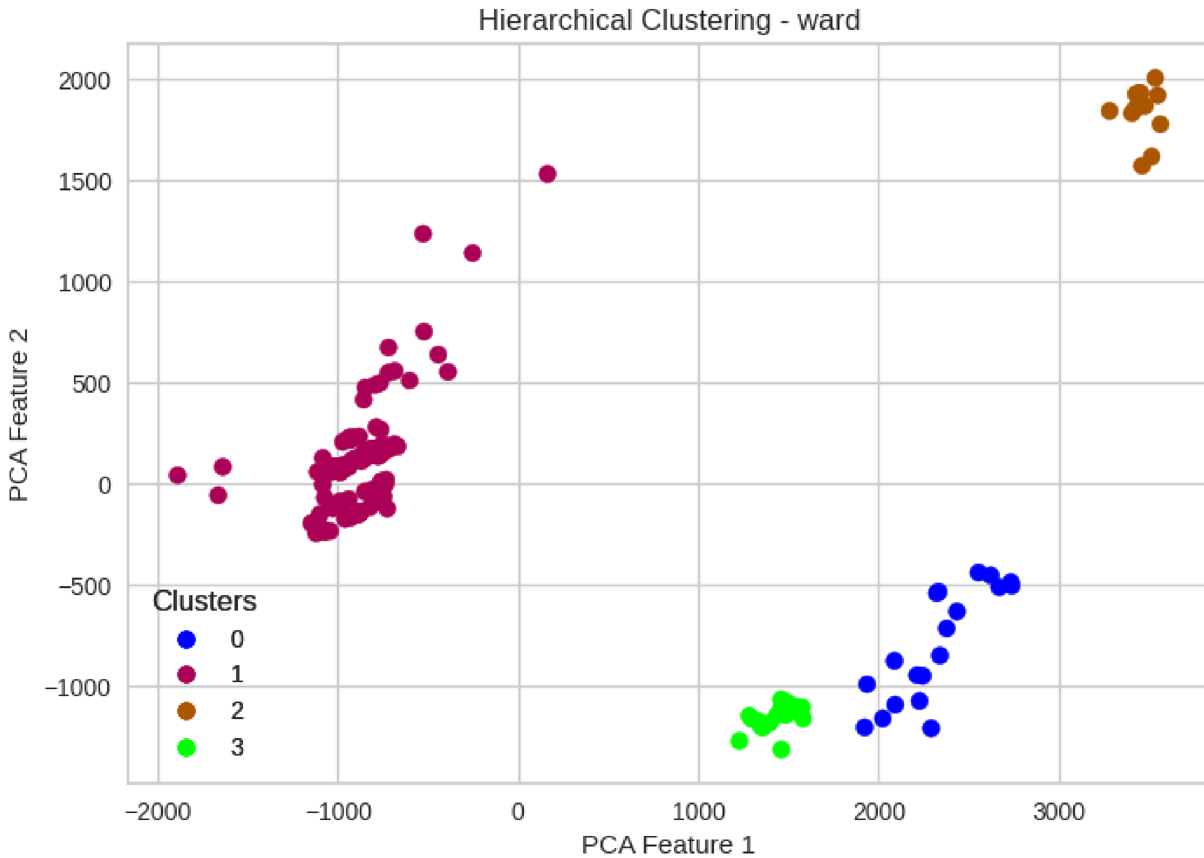
In [ ]:
```
#Calculating the Silhouette score to find the number of clusters

from yellowbrick.cluster import SilhouetteVisualizer

fig, ax = plt.subplots(2, 2, figsize=(15,8))
for i in [2, 3, 4, 5]:
    '''
    Create KMeans instances for different number of clusters
    '''
    km = KMeans(n_clusters=i, init='k-means++', n_init=10, max_iter=100, random_state=
    q, mod = divmod(i, 2)
    '''
    Create SilhouetteVisualizer instance with KMeans instance
    Fit the visualizer
    '''
    visualizer = SilhouetteVisualizer(km, colors='yellowbrick', ax=ax[q-1][mod])
    visualizer.fit(X)
```

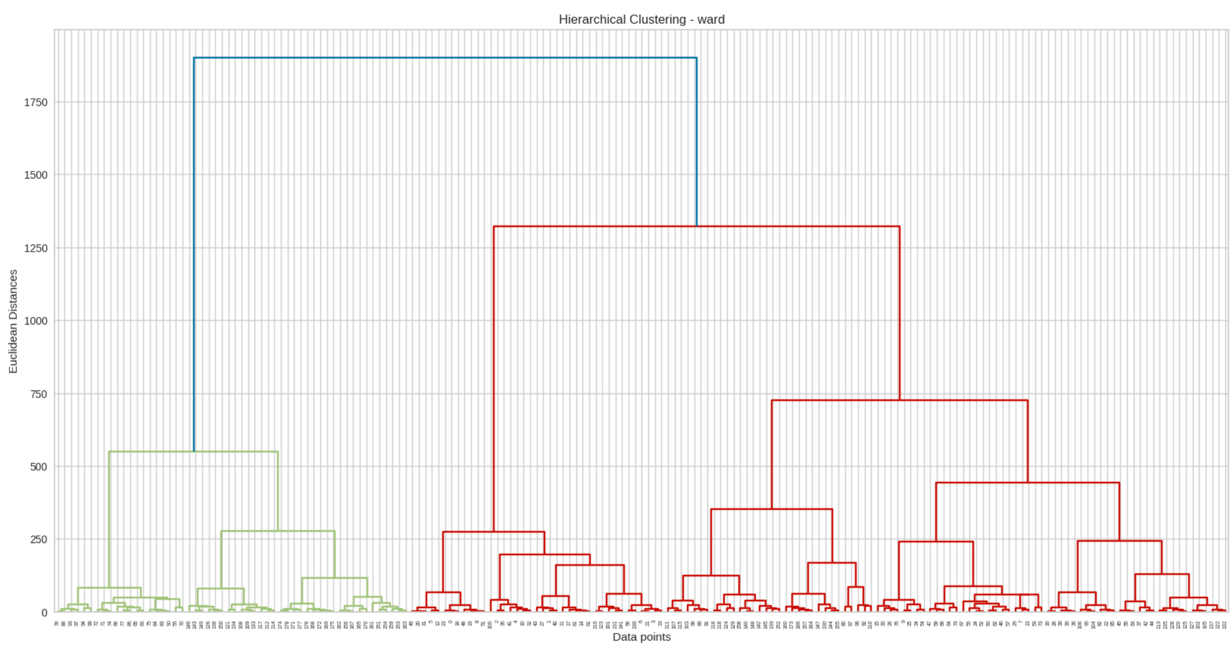


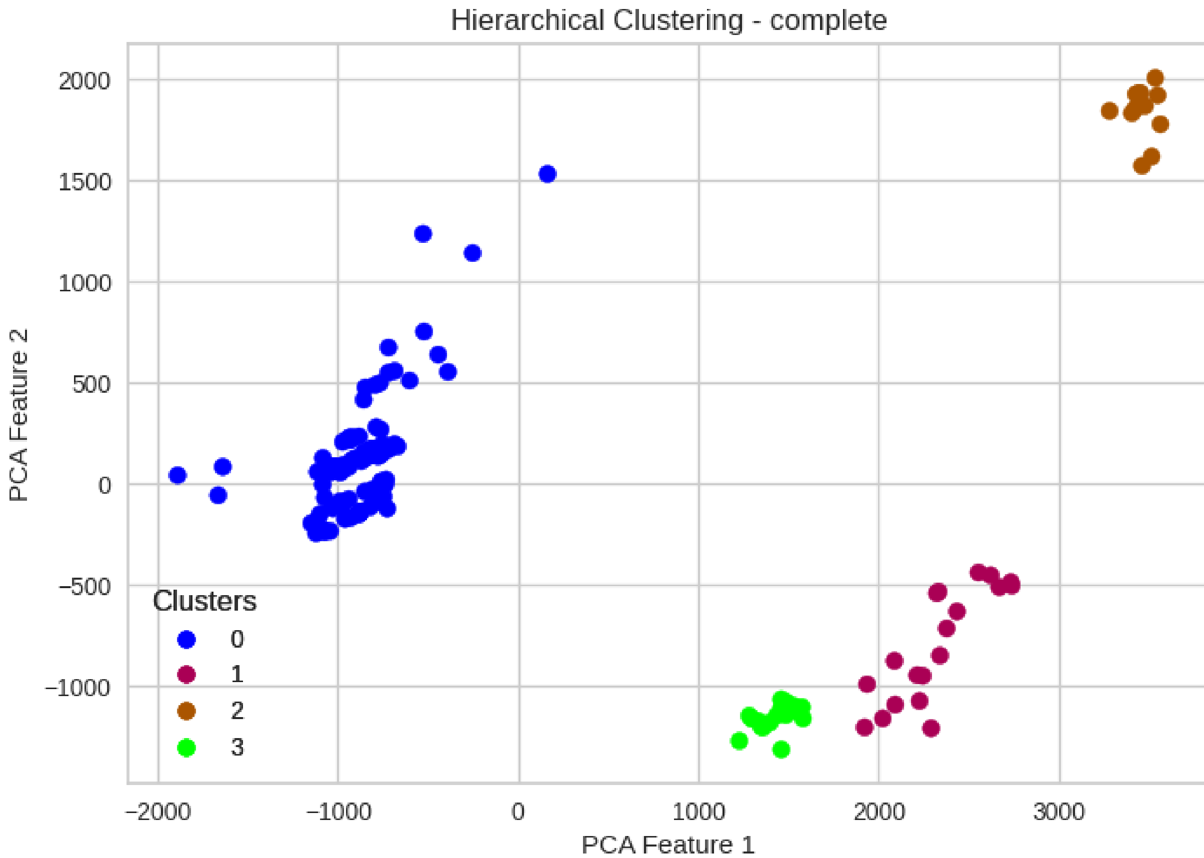
Here, we can see the plot where all the clusters have a Silhouette score more than the average score of the dataset (shown by the red dotted line) is with 4. Hence, number of clusters should be 4.

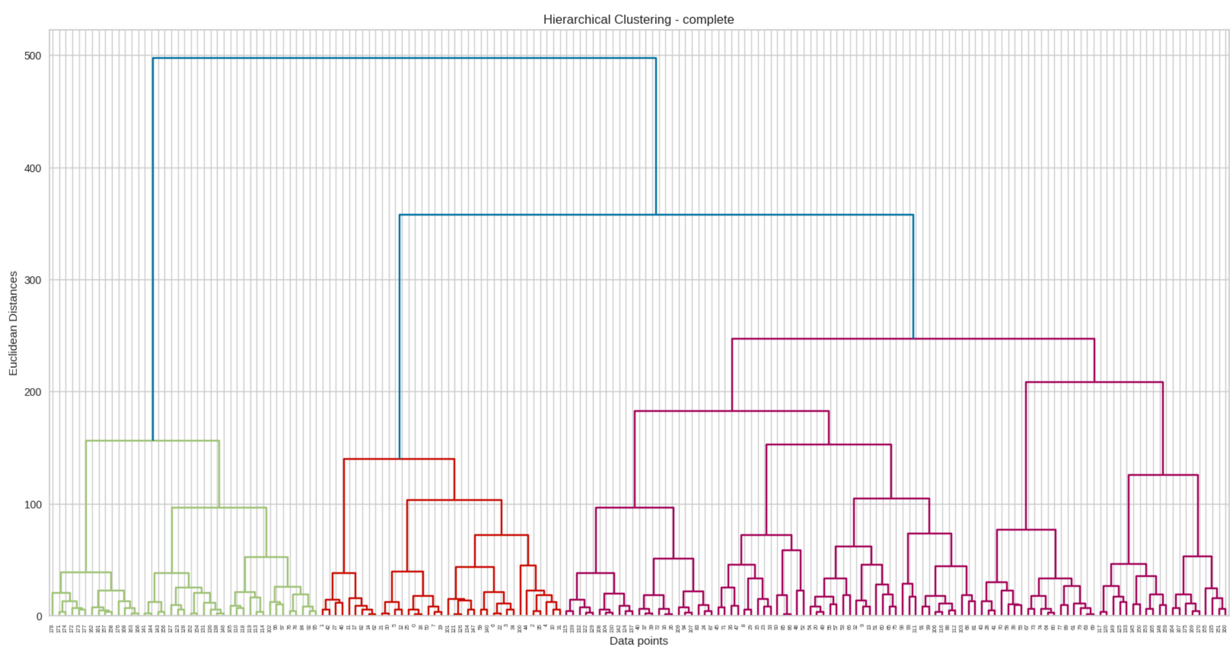
Hierarchical Clustering

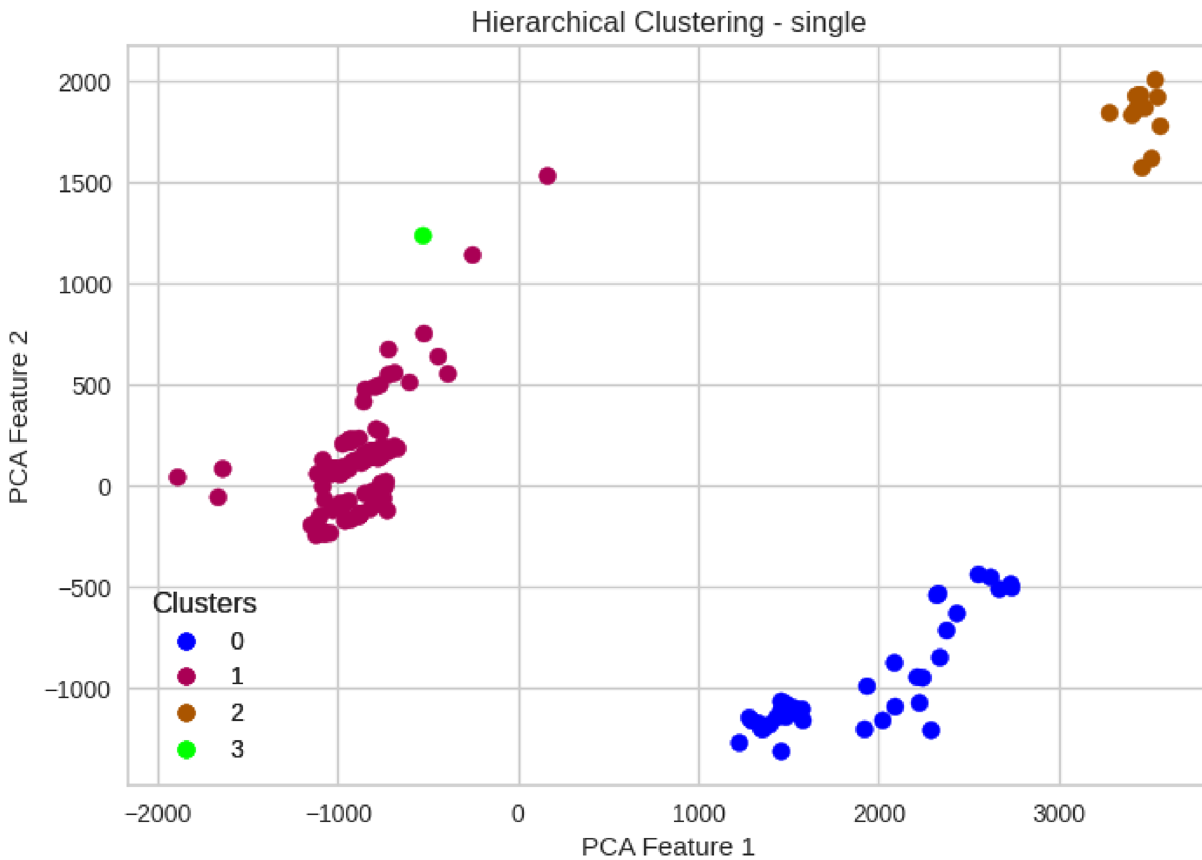
In [ ]:
```
import scipy.cluster.hierarchy as sch
from sklearn.preprocessing import normalize
from sklearn.cluster import AgglomerativeClustering

# Normalize the data
X = normalize(X)

# Fit agglomerative clustering model with various linkage methods
linkages = ['ward', 'complete', 'single', 'average']
for i in linkages:
  hc = AgglomerativeClustering(n_clusters=4, affinity='euclidean', linkage=i)
  labels = hc.fit_predict(X)
  plot_clusters(X_pca, labels, f'Hierarchical Clustering - {i}')

  # Plot Dendograms
  fig = plt.figure(figsize=(20, 10))
  dendrogram = sch.dendrogram(sch.linkage(hc.children_, method=i))
  plt.title(f'Hierarchical Clustering - {i}')
  plt.xlabel('Data points')
  plt.ylabel('Euclidean Distances')
  plt.show()
```

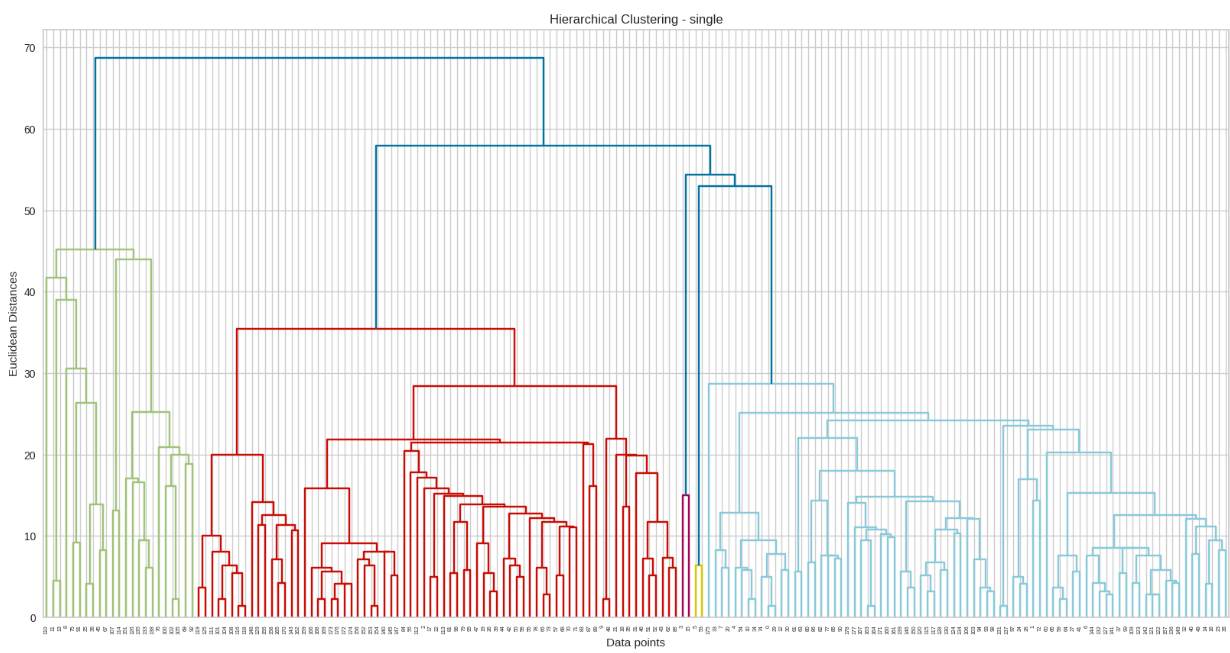

Hierarchical Clustering - ward
PCA Feature 1
PCA Feature 2
Clusters
0
1
2
3
−2000
−1000
0
1000
2000
3000
2000
1500
1000
500
0
−500
−1000

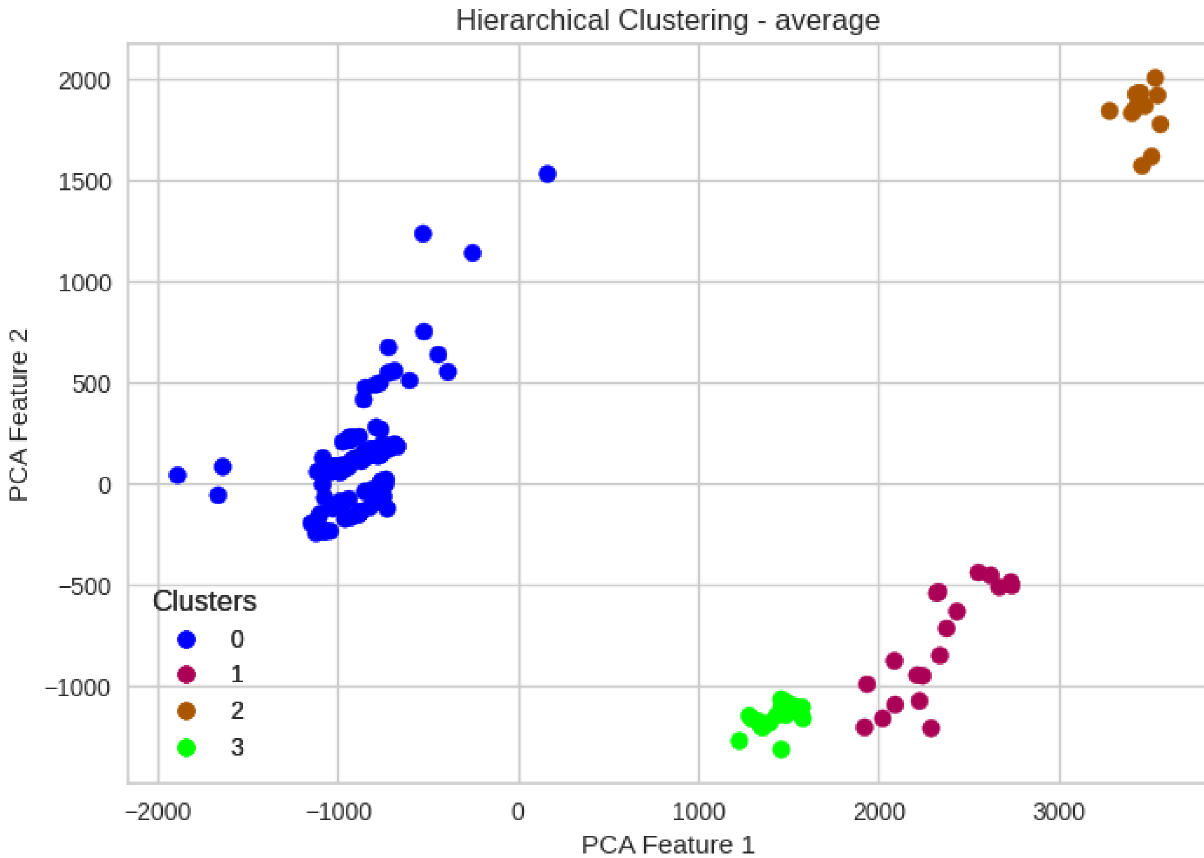

Hierarchical Clustering - ward
Euclidean Distances
Data points
1750
1500
1250
1000
750
500
250
0

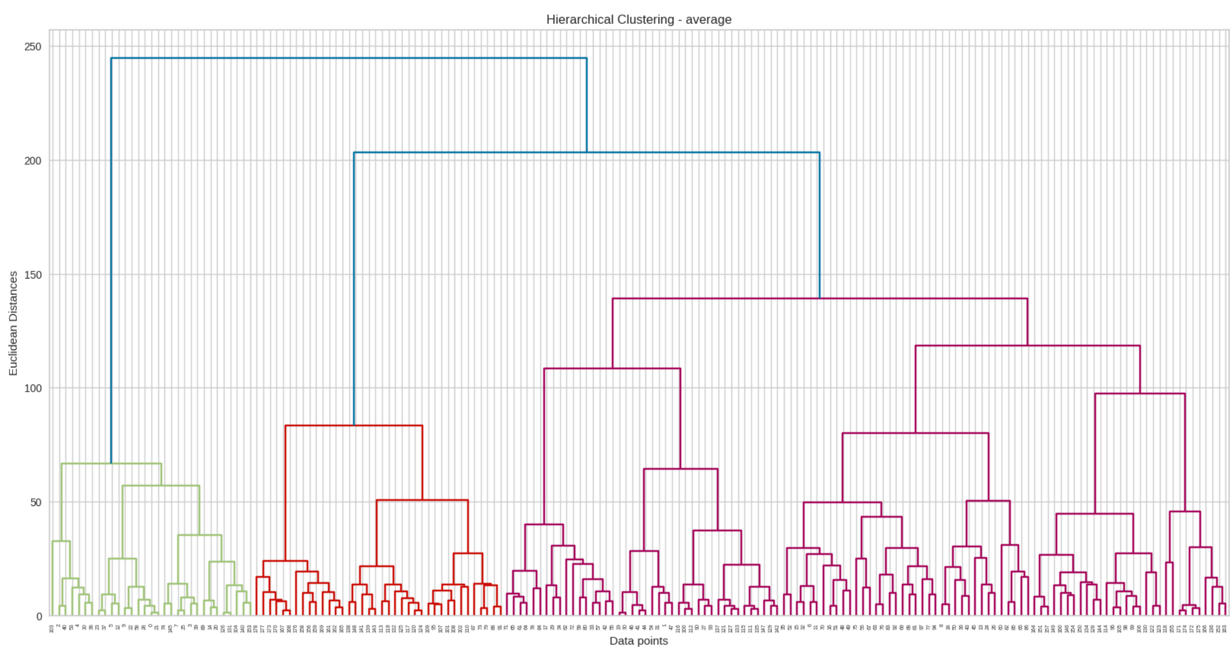

Hierarchical Clustering - complete
PCA Feature 2
PCA Feature 1
2000
1500
1000
500
0
−500
−1000
−2000
−1000
0
1000
2000
3000
Clusters
0
1
2
3


Hierarchical Clustering - complete
Euclidean Distances
Data points
500
400
300
200
100
0


Hierarchical Clustering - single
2000
1500
1000
500
0
−500
−1000
PCA Feature 2
−2000
−1000
0
1000
2000
3000
PCA Feature 1
Clusters
0
1
2
3


Hierarchical Clustering - single
70
60
50
40
30
20
10
0
Euclidean Distances
Data points



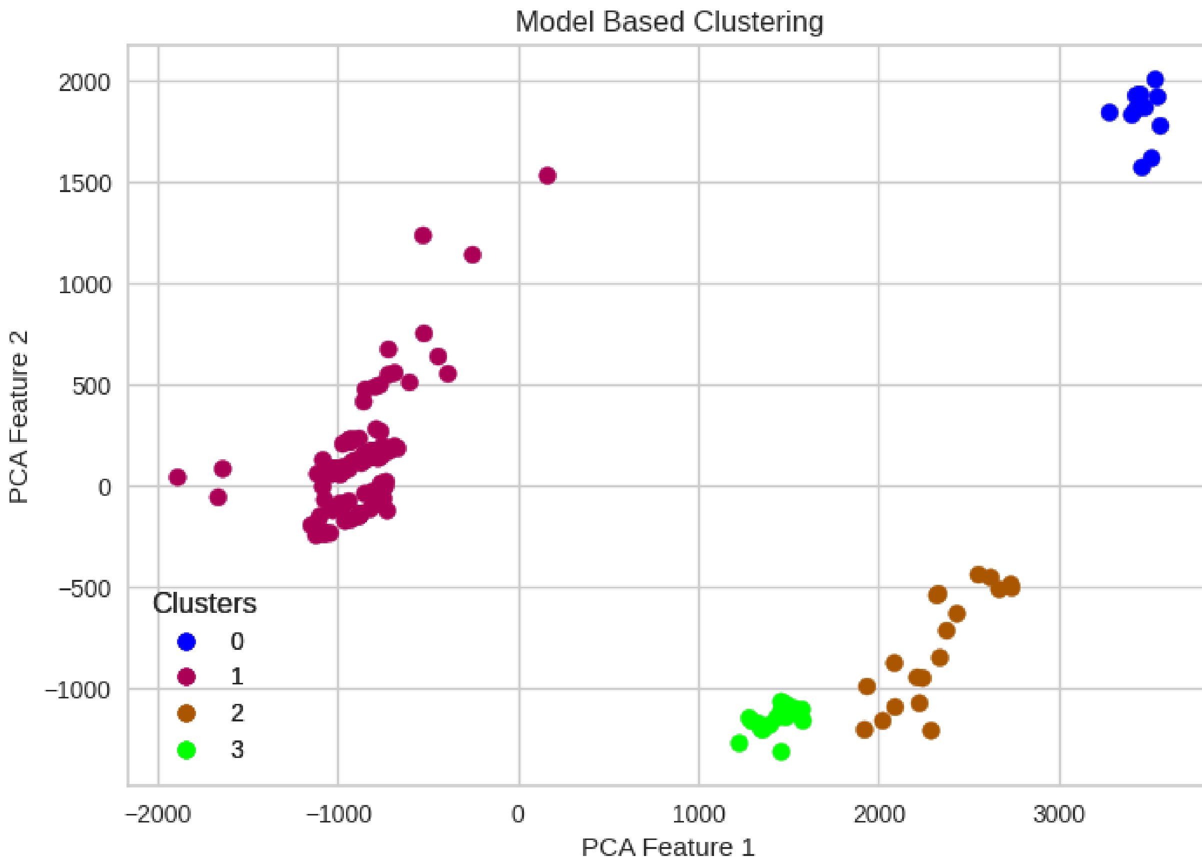


The best clusters are given by ward, complete or average clustering methods as shown in the visualizations. Euclidean distance metric is most commonly used when the predictor variables are continous and numeric.

Model Based

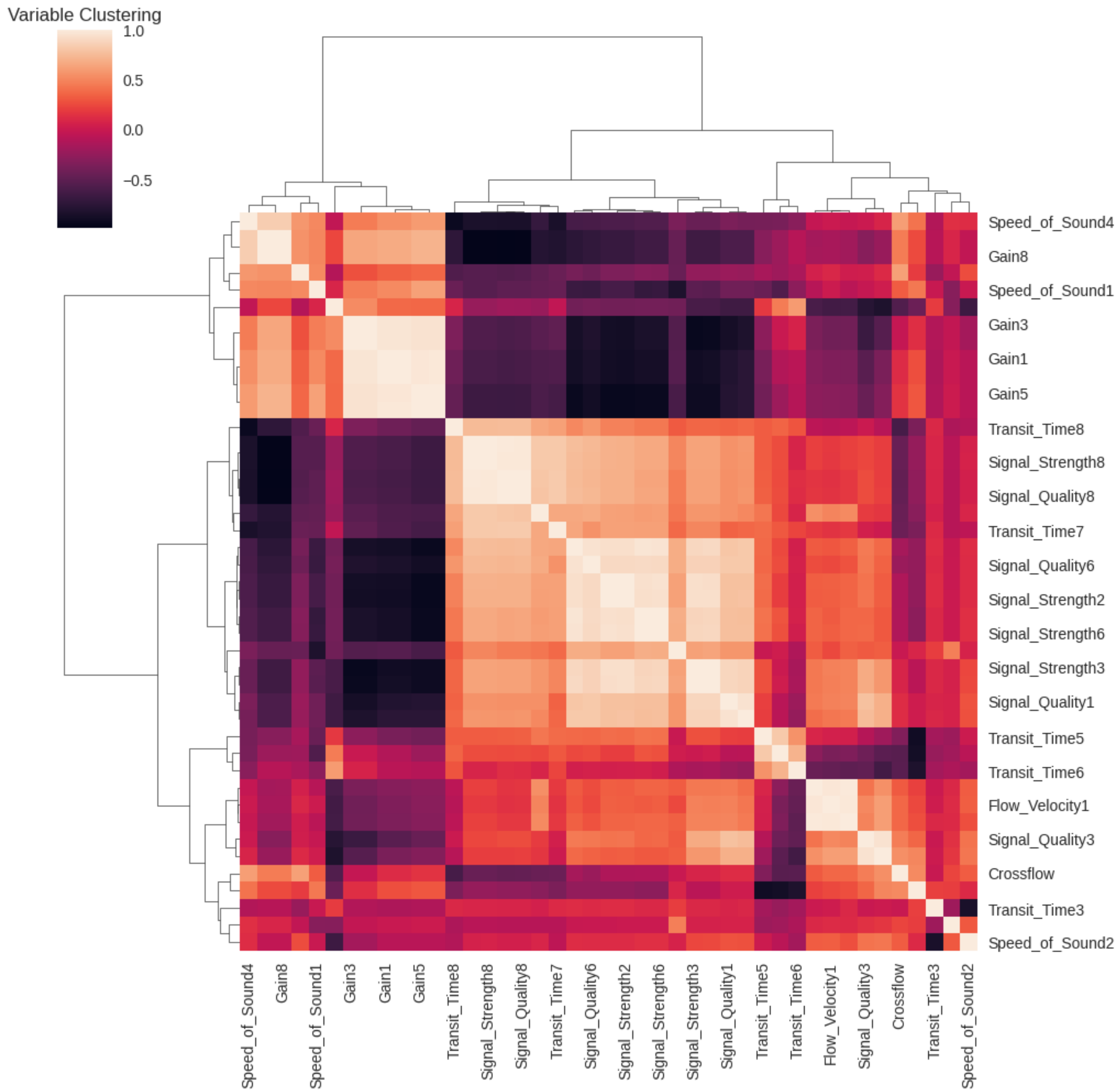
In [ ]:
```
from sklearn.mixture import GaussianMixture

# Fit Gaussian mixture model
gmm = GaussianMixture(n_components=4, random_state=0)
```

```
gmm.fit(X)
labels = gmm.predict(X)

# Visualize the clustering results
plot_clusters(X_pca, labels, 'Model Based Clustering')
```



Variable Clustering

In [ ]:
```
import seaborn as sns
from scipy.cluster import hierarchy

# Calculate the correlation matrix
df = pd.read_excel('Meter Data.xlsx', sheet_name='D')
X = df.drop(['Health_State_of_Meter'], axis=1)
X.head()
corr = X.corr()

linkage = hierarchy.ward(corr)
sns.clustermap(corr, row_linkage=linkage, col_linkage=linkage)
plt.title("Variable Clustering")
plt.show()
```

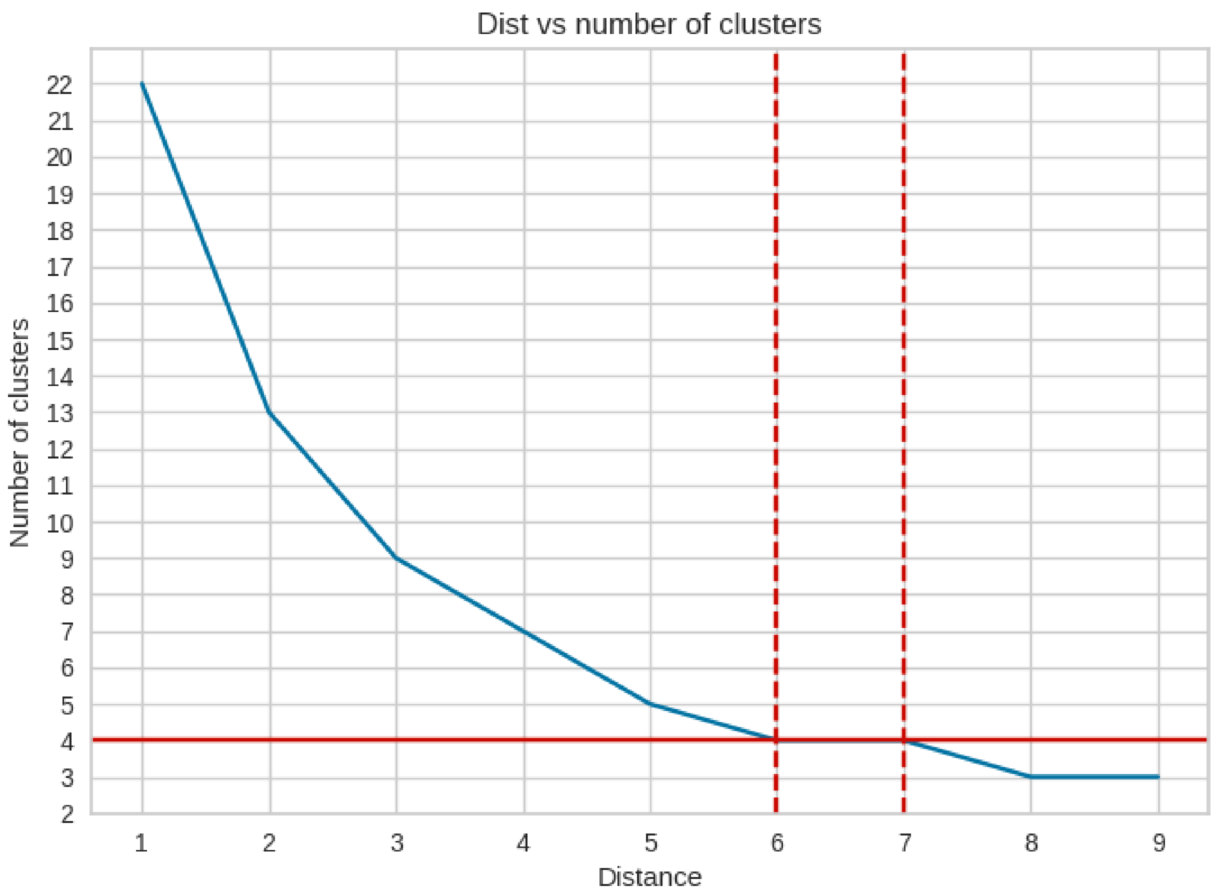


In [ ]:

```python
from scipy.cluster.hierarchy import fcluster

# find the optimal max_distance to achieve 4 clusters
max_distances = range(1, 10)
cluster_len = {}
for max_dist in max_distances:
    clusters = fcluster(linkage, t=max_dist, criterion='distance')
    print(f"Max dist: {max_dist}, Unique cluster classes: {list(np.unique(clusters))}'
    cluster_len[max_dist] = len(list(np.unique(clusters)))
    # print("Variable Clusters: :\n", pd.DataFrame({'Variable': X.columns, 'Cluster':
```

```
Max dist: 1, Unique cluster classes: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14,
15, 16, 17, 18, 19, 20, 21, 22]
Max dist: 2, Unique cluster classes: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13]
Max dist: 3, Unique cluster classes: [1, 2, 3, 4, 5, 6, 7, 8, 9]
Max dist: 4, Unique cluster classes: [1, 2, 3, 4, 5, 6, 7]
Max dist: 5, Unique cluster classes: [1, 2, 3, 4, 5]
Max dist: 6, Unique cluster classes: [1, 2, 3, 4]
Max dist: 7, Unique cluster classes: [1, 2, 3, 4]
Max dist: 8, Unique cluster classes: [1, 2, 3]
Max dist: 9, Unique cluster classes: [1, 2, 3]
```

In [ ]:
```
plt.plot(cluster_len.keys(), cluster_len.values())
plt.title("Dist vs number of clusters")
plt.xlabel('Distance')
plt.yticks(np.arange(min(cluster_len.values()) -1, max(cluster_len.values()) + 1, step
# specifying horizontal line type
plt.axhline(y = 4, color = 'r', linestyle = '-')
plt.axvline(x = 6, color = 'r', linestyle = '--')
plt.axvline(x = 7, color = 'r', linestyle = '--')
plt.ylabel('Number of clusters')
plt.show()
plt.show()
```



The max distance 6 or 7 gives us the required number of clusters as shown.

In [ ]:
```
# create the cluster labels for each variable
max_d = 6
clusters = fcluster(linkage, t=max_d, criterion='distance')
print(f"Unique cluster classes: {list(np.unique(clusters))}")
print("Variable Clusters: :\n", pd.DataFrame({'Variable': X.columns, 'Cluster': cluste
```

```
Unique cluster classes: [1, 2, 3, 4]
Variable Clusters: :
             Variable  Cluster
0      Profile_Factor        1
1            Symmetry        4
2           Crossflow        4
3      Flow_Velocity1        4
4      Flow_Velocity2        4
5      Flow_Velocity3        4
6      Flow_Velocity4        2
7     Speed_of_Sound1        1
8     Speed_of_Sound2        4
9     Speed_of_Sound3        4
10    Speed_of_Sound4        1
11   Signal_Strength1        2
12   Signal_Strength2        2
13   Signal_Strength3        2
14   Signal_Strength4        2
15   Signal_Strength5        2
16   Signal_Strength6        2
17   Signal_Strength7        2
18   Signal_Strength8        2
19    Signal_Quality1        2
20    Signal_Quality2        2
21    Signal_Quality3        4
22    Signal_Quality4        4
23    Signal_Quality5        2
24    Signal_Quality6        2
25    Signal_Quality7        2
26    Signal_Quality8        2
27              Gain1        1
28              Gain2        1
29              Gain3        1
30              Gain4        1
31              Gain5        1
32              Gain6        1
33              Gain7        1
34              Gain8        1
35      Transit_Time1        2
36      Transit_Time2        3
37      Transit_Time3        4
38      Transit_Time4        1
39      Transit_Time5        3
40      Transit_Time6        3
41      Transit_Time7        2
42      Transit_Time8        2
```

Variable Selection

In [ ]:

```
# Import necessary libraries
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.ensemble import RandomForestClassifier

# Load the data into a pandas dataframe
df = pd.read_csv('Data.csv')

# Separate the predictor variables and the target variable
X = df.drop('Health_State_of_Meter', axis=1)
y = df['Health_State_of_Meter']
```

```python
# Convert the categorical target variable to numerical values
y = y.map({'Healthy': 0, 'Gas injection': 1, 'Installation effects': 2, 'Waxing': 3})
```

In [ ]:

```python
# ANOVA F-test for feature selection - variable statistics-based method
k = 10
selector = SelectKBest(score_func=f_classif, k=k)
selector.fit_transform(X, y)
X_selected = X.columns[selector.get_support()].tolist()
# Print the selected variables
print(f'Selected features using ANOVA F-test: {X_selected}')
```

```
Selected features using ANOVA F-test: ['Flow_Velocity4', 'Speed_of_Sound4', 'Signal_S
trength7', 'Signal_Strength8', 'Signal_Quality5', 'Signal_Quality7', 'Signal_Quality
8', 'Gain7', 'Gain8', 'Transit_Time7']
```

In [ ]:

```python
from sklearn.model_selection import train_test_split
from lazypredict.Supervised import LazyClassifier

# find the accuracy of the selected features

x_tr, x_ts, y_tr, y_ts = train_test_split(X[X_selected], y, test_size=0.1, random_stat
clf = LazyClassifier(verbose=0,ignore_warnings=True, custom_metric=None)
models,predictions = clf.fit(x_tr, x_ts, y_tr, y_ts)

print(models[["Accuracy", "F1 Score", "Time Taken"]][:10])
```

```
100%|██████████| 29/29 [00:01<00:00, 25.08it/s]
                        Accuracy  F1 Score  Time Taken
Model
AdaBoostClassifier          0.89      0.89        0.11
RandomForestClassifier      0.89      0.89        0.20
LGBMClassifier              0.89      0.89        0.09
LinearSVC                   0.83      0.83        0.03
XGBClassifier               0.83      0.83        0.09
ExtraTreeClassifier         0.83      0.83        0.01
ExtraTreesClassifier        0.83      0.83        0.15
SGDClassifier               0.89      0.89        0.02
LabelPropagation            0.83      0.80        0.02
LabelSpreading              0.83      0.80        0.02
```

In [ ]:

```python
# Random Forest Classifier for feature selection - model based
model = RandomForestClassifier()
model.fit(X, y)
importance = model.feature_importances_
indices = importance.argsort()[-k:][::-1]
selected_features = X.columns[indices]
X_selected = selected_features.tolist()

# Print the selected variables
print(f'Selected features using Random Forest Classifier: {X_selected}')
```

```
Selected features using Random Forest Classifier: ['Transit_Time8', 'Signal_Quality
1', 'Transit_Time7', 'Signal_Strength8', 'Gain8', 'Speed_of_Sound4', 'Gain3', 'Gain
7', 'Signal_Strength7', 'Gain2']
```

In [ ]:

```python
from sklearn.model_selection import train_test_split
from lazypredict.Supervised import LazyClassifier
```

```python
# find the accuracy of the selected features

x_tr, x_ts, y_tr, y_ts = train_test_split(X[X_selected], y, test_size=0.1, random_stat
clf = LazyClassifier(verbose=0,ignore_warnings=True, custom_metric=None)
models,predictions = clf.fit(x_tr, x_ts, y_tr, y_ts)

print(models[["Accuracy", "F1 Score", "Time Taken"]][:10])
```

```
100%|██████████| 29/29 [00:01<00:00, 21.94it/s]
                        Accuracy  F1 Score  Time Taken
Model
LGBMClassifier              0.94      0.94        0.27
ExtraTreesClassifier        0.94      0.94        0.16
BaggingClassifier           0.94      0.94        0.05
LabelSpreading              0.94      0.94        0.02
LabelPropagation            0.94      0.94        0.02
RandomForestClassifier      0.94      0.94        0.18
XGBClassifier               0.94      0.94        0.09
ExtraTreeClassifier         0.89      0.89        0.01
KNeighborsClassifier        0.89      0.89        0.01
DecisionTreeClassifier      0.89      0.89        0.01
```

We can conclude that the variables selected by the model based are giving better accuracies as compared to variable statistics-based method.