ELECTRIC CAR DATA ANALYSIS

CONTEXT

The data describes various electric car models with features like acceleration, range, and price. We want to analyze this data to see what features are most important to potential buyers (e.g., long range, fast charging, affordability). This will help both consumers make informed choices and manufacturers understand what electric car features to prioritize.

OBJECTIVE

The main objective of analyzing this electric car data is to understand what features are most important to potential buyers when choosing an electric car. This will be achieved by:

- Identifying key factors influencing purchase decisions (e.g., range, price, performance).
- Comparing various electric car models based on these factors.

PROBLEM STATEMENT

Problem Statement: Analyze factors influencing electric car selection for potential buyers.

IMPORT LIBRARIES

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

LOAD DATASET

In [2]:
```
df=pd.read_csv("ElectricCarData.csv")
df
```

Out[2]:

	Brand	Model	AccelSec	TopSpeed_KmH	Range_Km	Efficiency_WhKm	FastChar
0	Tesla	Model 3 Long Range Dual Motor	4.6	233	450	161	
1	Volkswagen	ID.3 Pure	10.0	160	270	167	
2	Polestar	2	4.7	210	400	181	
3	BMW	iX3	6.8	180	360	206	
4	Honda	e	9.5	145	170	168	
...	...	...	...	...	...	...	
98	Nissan	Ariya 63kWh	7.5	160	330	191	
99	Audi	e-tron S Sportback 55 quattro	4.5	210	335	258	
100	Nissan	Ariya e-4ORCE 63kWh	5.9	200	325	194	
101	Nissan	Ariya e-4ORCE 87kWh Performance	5.1	200	375	232	
102	Byton	M-Byte 95 kWh 2WD	7.5	190	400	238	

103 rows × 14 columns

INFORMATION ABOUT DATASET

The dataset provided contains information about different electric vehicles. Here's a breakdown of the columns:

- **Brand:** The brand or manufacturer of the electric vehicle.
- **Model:** The model name of the electric vehicle.
- **AccelSec:** Acceleration time from 0 to 100 km/h in seconds.
- **TopSpeed_KmH:** Top speed of the vehicle in kilometers per hour.
- **Range_Km:** The range the vehicle can travel on a single charge in kilometers.
- **Efficiency_WhKm:** Energy efficiency of the vehicle measured in watt-hours per kilometer.
- **FastCharge_KmH:** Fast charging speed in kilometers per hour.

- **RapidCharge:** Indicates if the vehicle supports rapid charging or not.
- **PowerTrain:** Type of powertrain used in the vehicle.(transmits power from the engine to the wheels)
- **PlugType:** The type of plug used for charging.
- **BodyStyle:** The body style of the vehicle (e.g., sedan, hatchback).
- **Segment:** Segment of the vehicle in terms of size or market positioning.
- **Seats**: Number of seats in the vehicle.
- **PriceEuro:** Price of the vehicle in Euros.

In [70]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103 entries, 0 to 102
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Brand            103 non-null    object 
 1   Model            103 non-null    object 
 2   AccelSec         103 non-null    float64
 3   TopSpeed_KmH     103 non-null    int64  
 4   Range_Km         103 non-null    int64  
 5   Efficiency_WhKm  103 non-null    int64  
 6   FastCharge_KmH   103 non-null    object 
 7   RapidCharge      103 non-null    object 
 8   PowerTrain       103 non-null    object 
 9   PlugType         103 non-null    object 
 10  BodyStyle        103 non-null    object 
 11  Segment          103 non-null    object 
 12  Seats            103 non-null    int64  
 13  PriceEuro        103 non-null    int64  
dtypes: float64(1), int64(5), object(8)
memory usage: 11.4+ KB
```

CHECK NULL VALUES

In [71]:
```
df.isnull().sum()
```

Out[71]:
```
Brand              0
Model              0
AccelSec           0
TopSpeed_KmH       0
Range_Km           0
Efficiency_WhKm    0
FastCharge_KmH     0
RapidCharge        0
PowerTrain         0
PlugType           0
BodyStyle          0
Segment            0
Seats              0
PriceEuro          0
dtype: int64
```

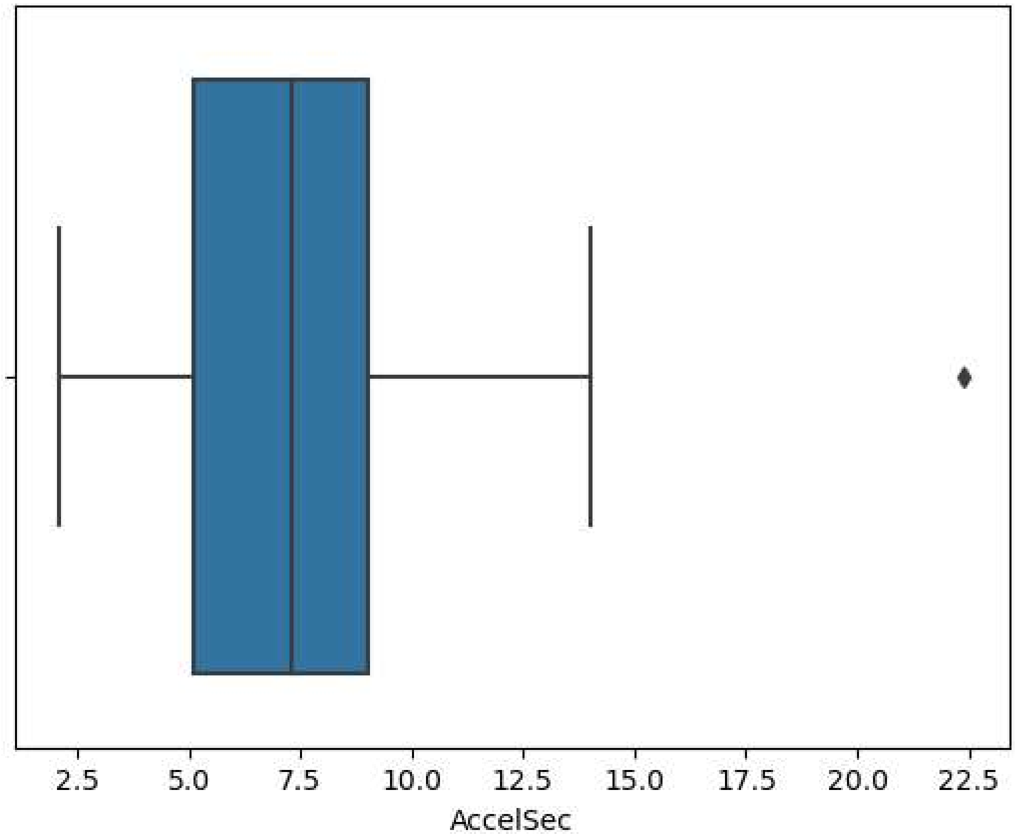
CHECK DUPLICATED VALUES

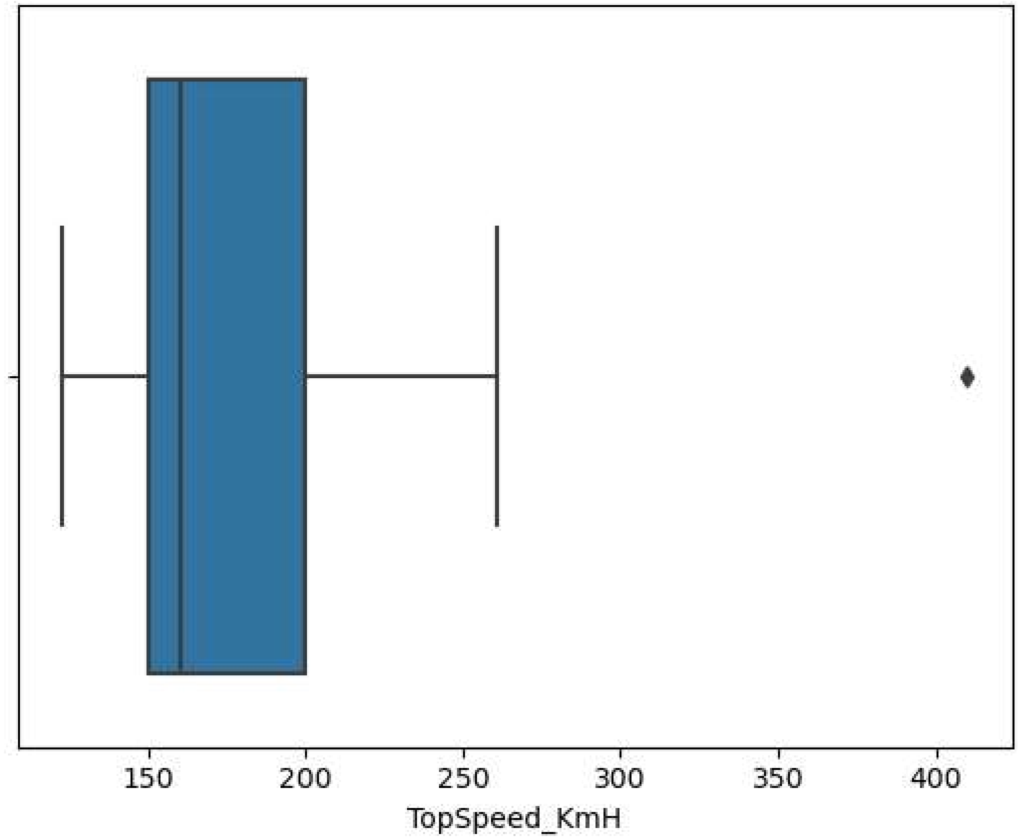
In [72]:
```
df[df.duplicated()].count()
```

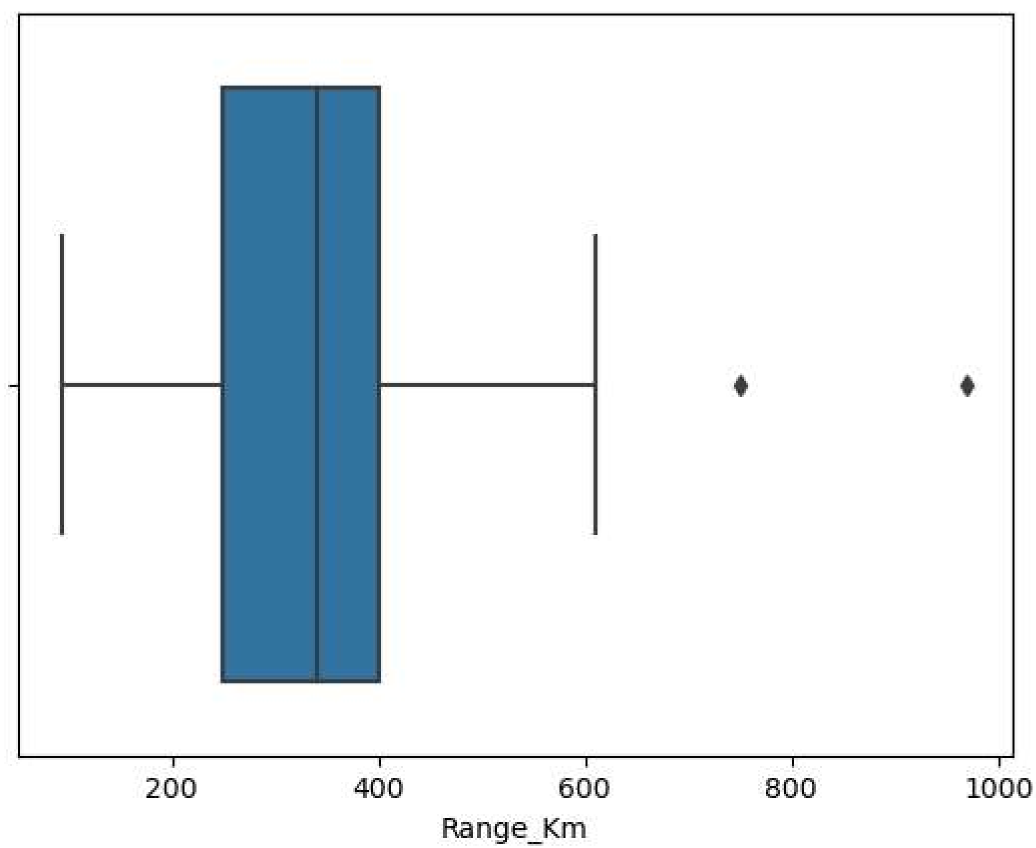
Out[72]:
```
Brand              0
Model              0
AccelSec           0
TopSpeed_KmH       0
Range_Km           0
Efficiency_WhKm    0
FastCharge_KmH     0
RapidCharge        0
PowerTrain         0
PlugType           0
BodyStyle          0
Segment            0
Seats              0
PriceEuro          0
dtype: int64
```

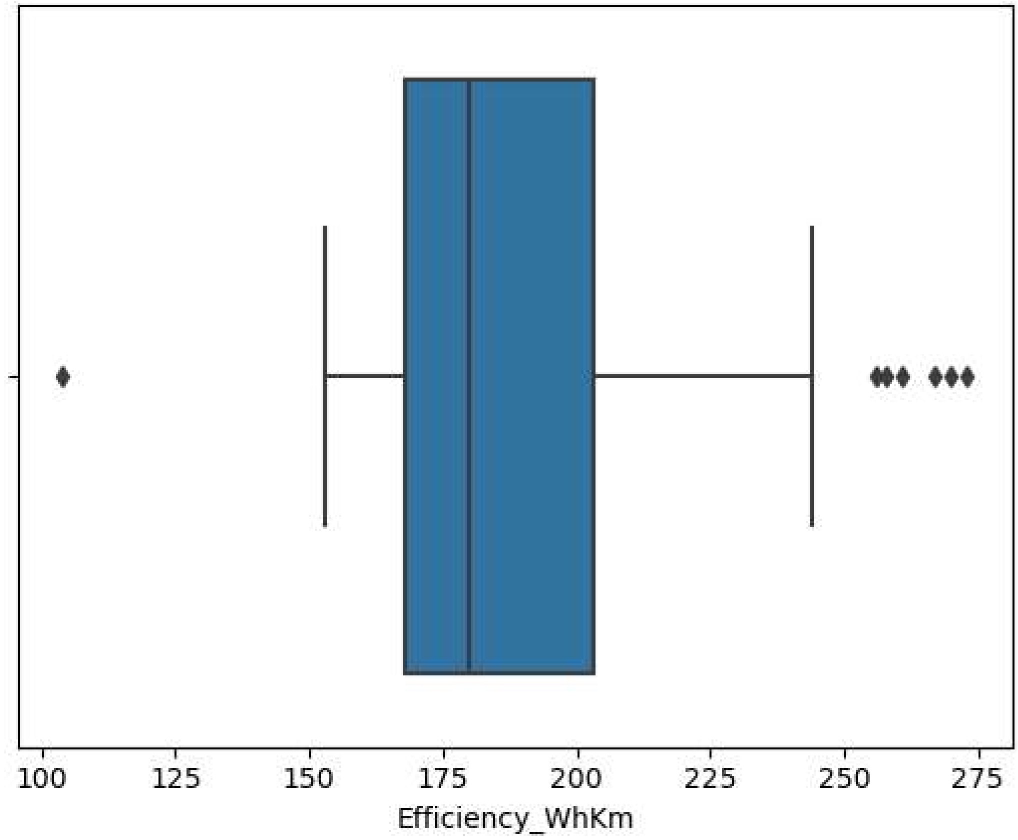
CHECK OUTLIERS

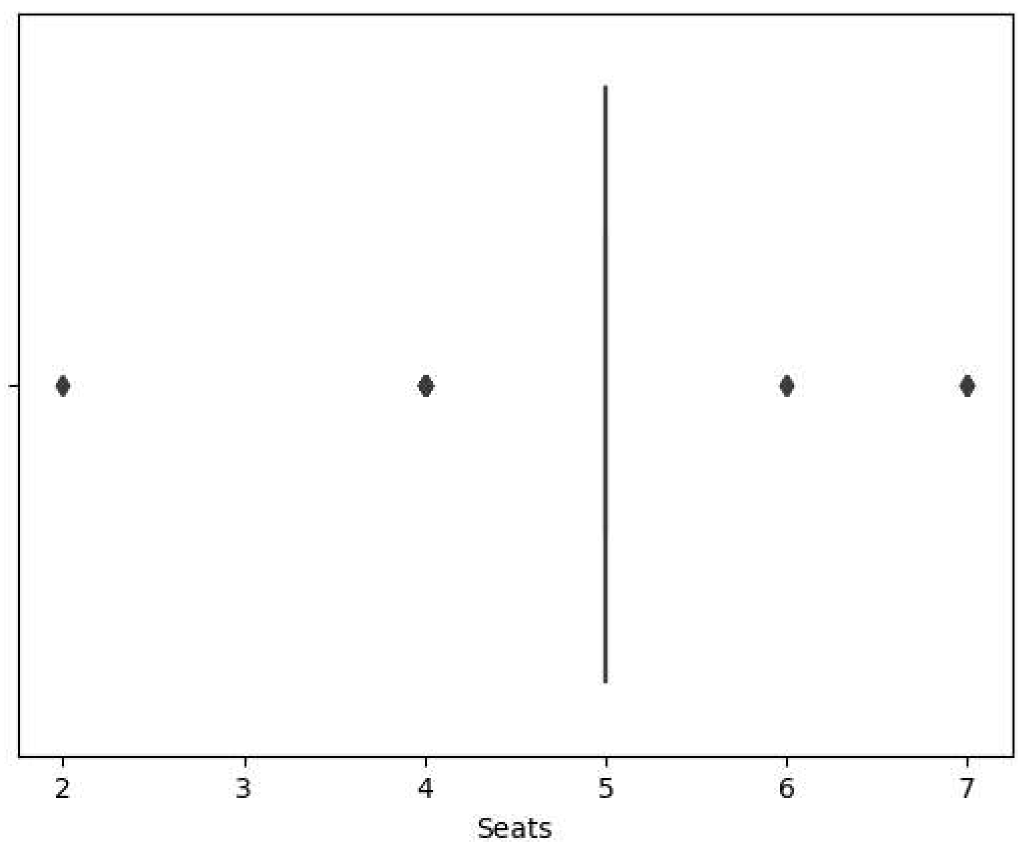
In [73]:
```
for i in df.select_dtypes(['int','float']):
    sns.boxplot(data=df,x=i)
    plt.show()
```

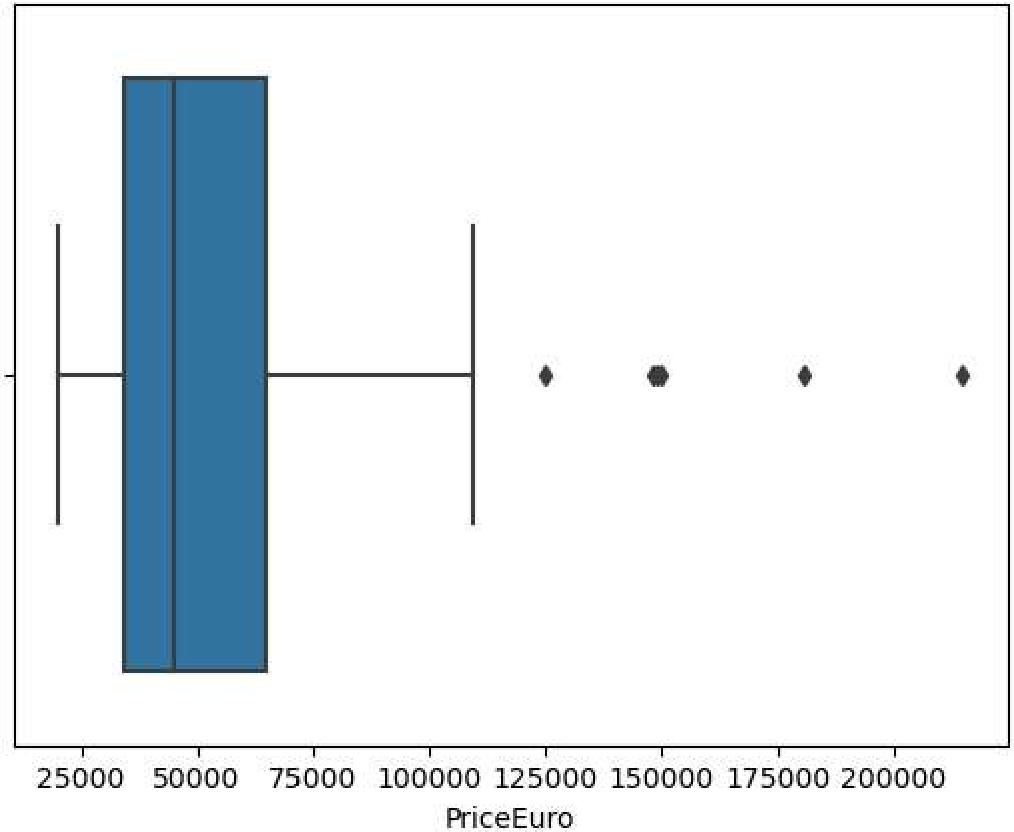



150
200
250
300
350
400
TopSpeed_KmH


200
400
600
800
1000
Range_Km


100
125
150
175
200
225
250
275
Efficiency_WhKm


2
3
4
5
6
7
Seats

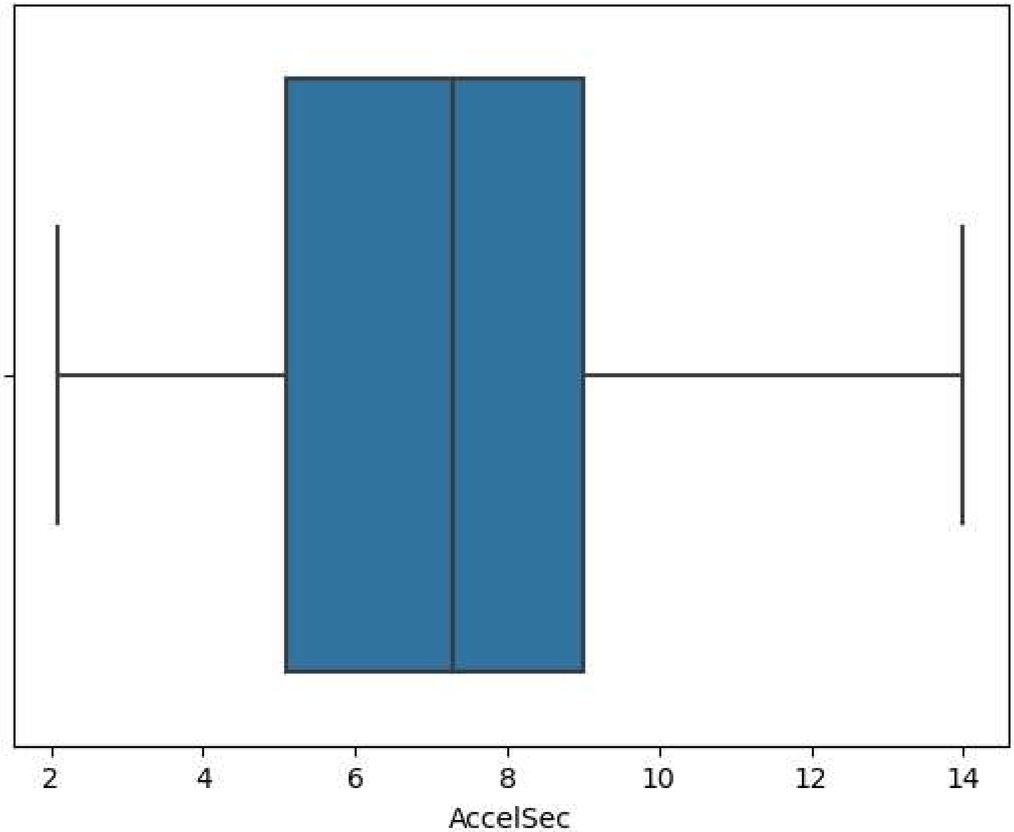


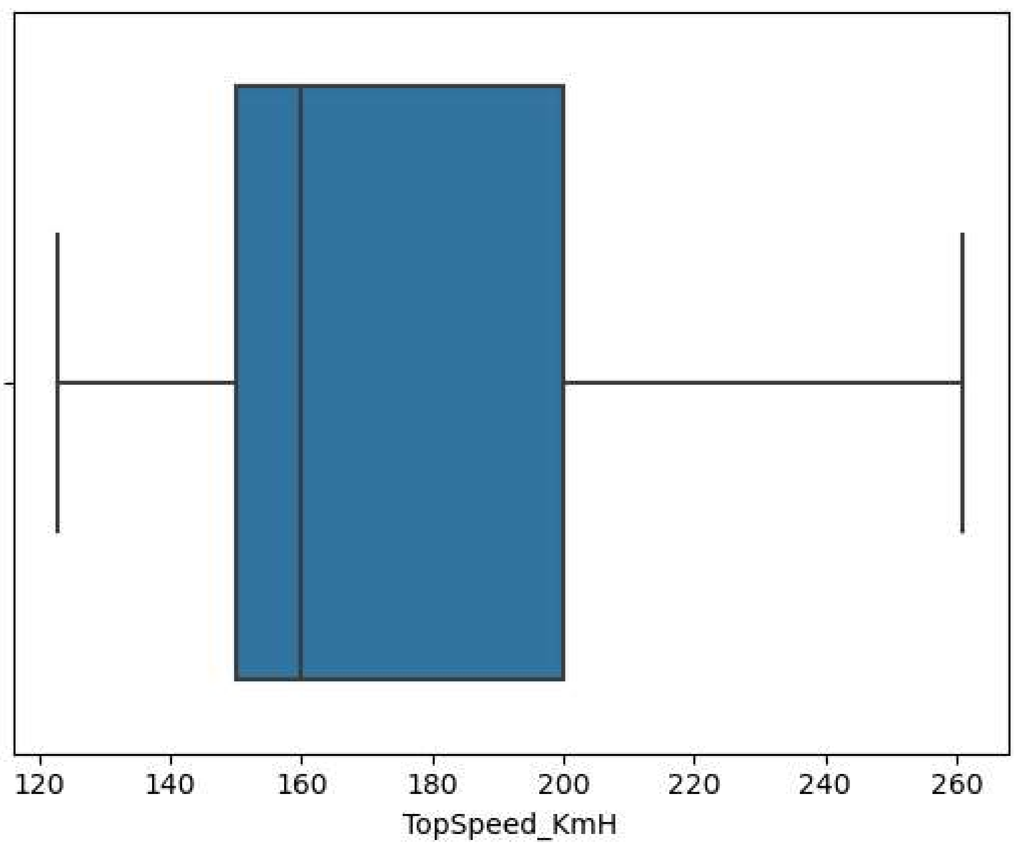
OUTLIERS TREATMENT

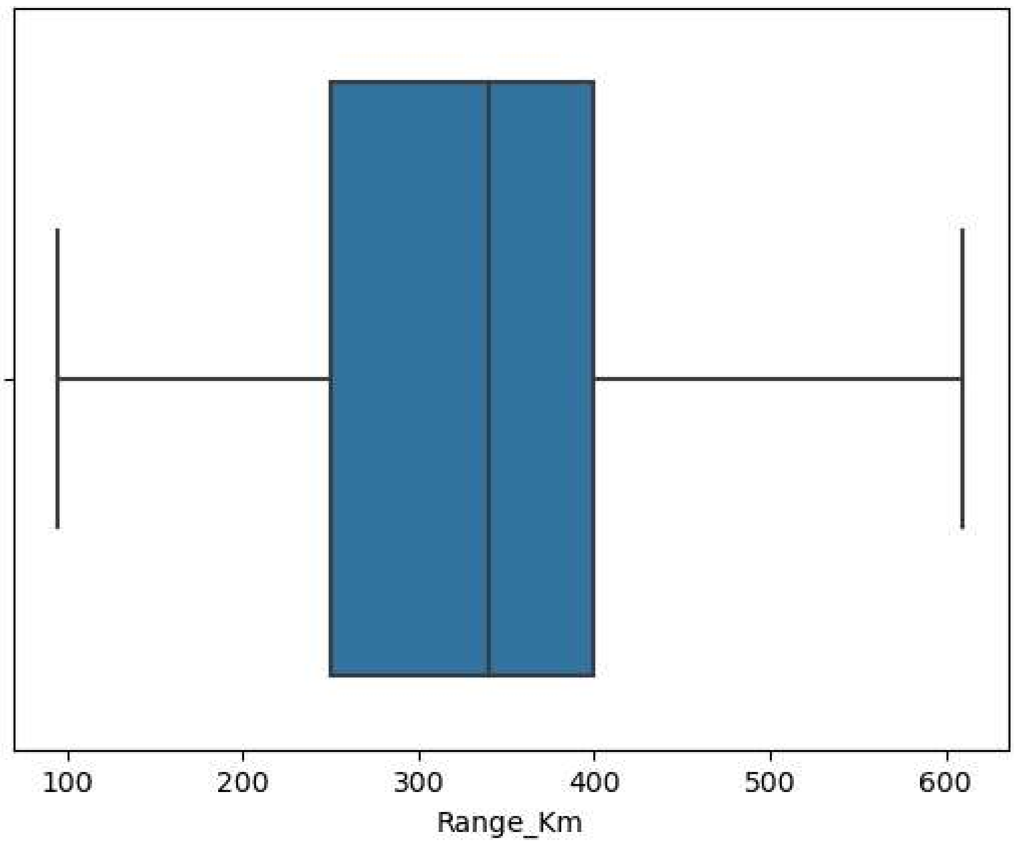
In [3]:
```
def outliers_treatment(col):
     Q1=df[col].quantile(0.25)
     Q3=df[col].quantile(0.75)
     IQR= Q3 - Q1
     UB=Q3+1.5*IQR
     LB=Q1-1.5*IQR
     Upper_Outlier=df[col]>UB
     Lower_Outlier=df[col]<LB
     df.loc[Upper_Outlier,col]=df[col].median()
     df.loc[Lower_Outlier,col]=df[col].median()
```

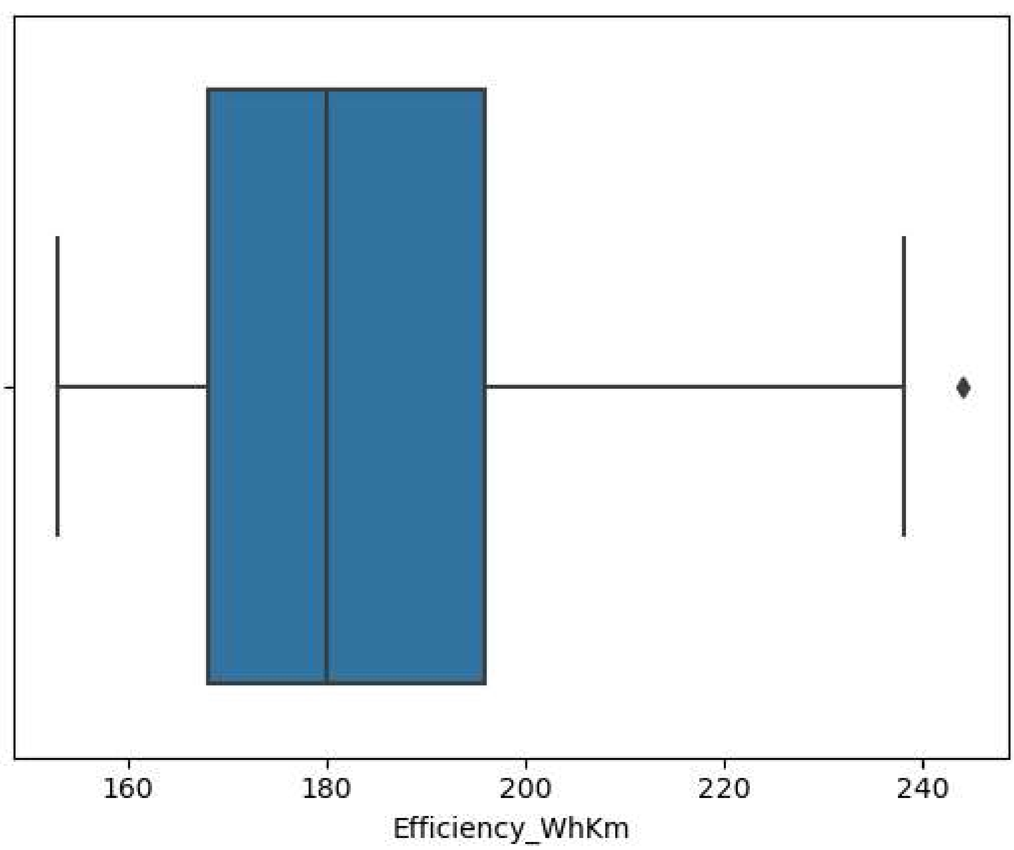
In [4]:
```
for i in df.select_dtypes(['int','float']):
 outliers_treatment(i)
```

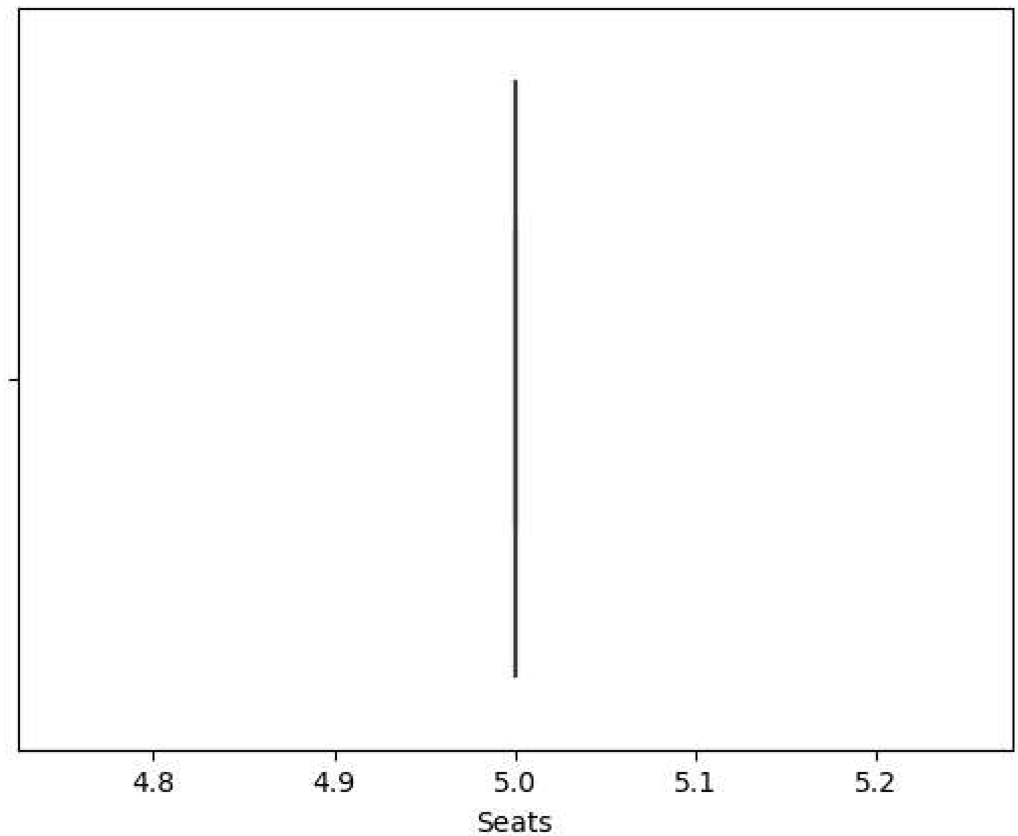
In [5]:
```
for i in df.select_dtypes(['int','float']):
    sns.boxplot(data=df,x=i)
    plt.show()
```

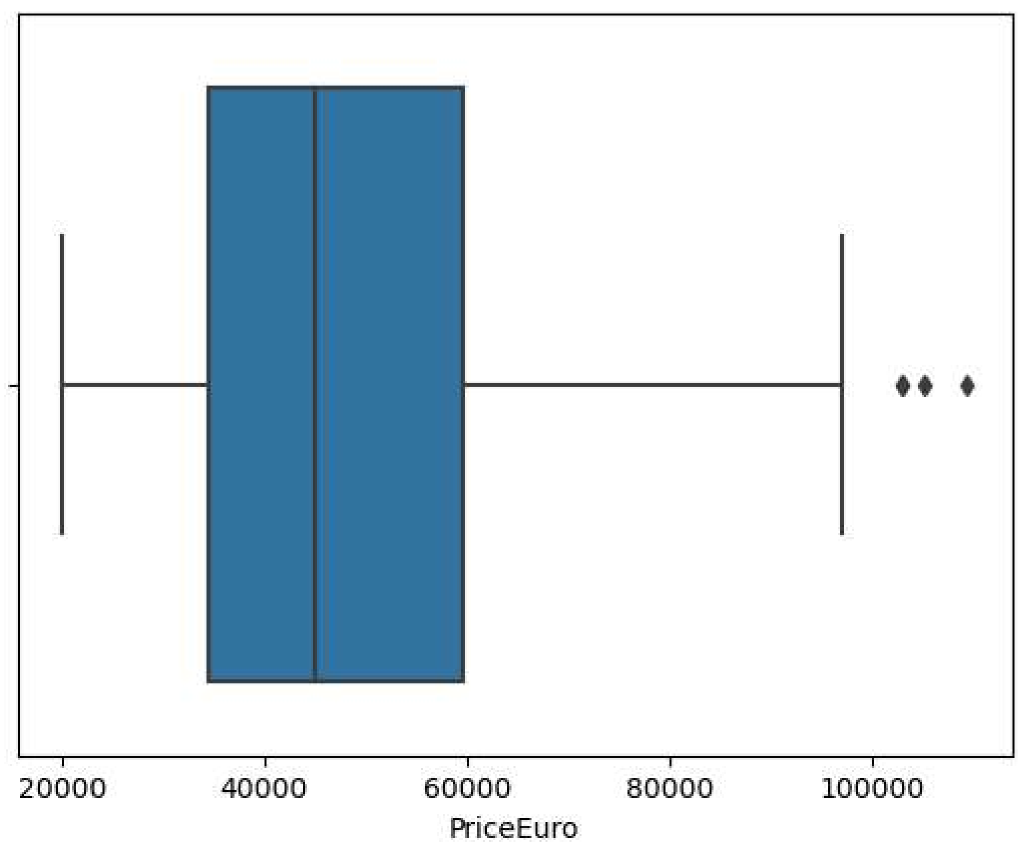





100
200
300
400
500
600
Range_Km


160
180
200
220
240
Efficiency_WhKm

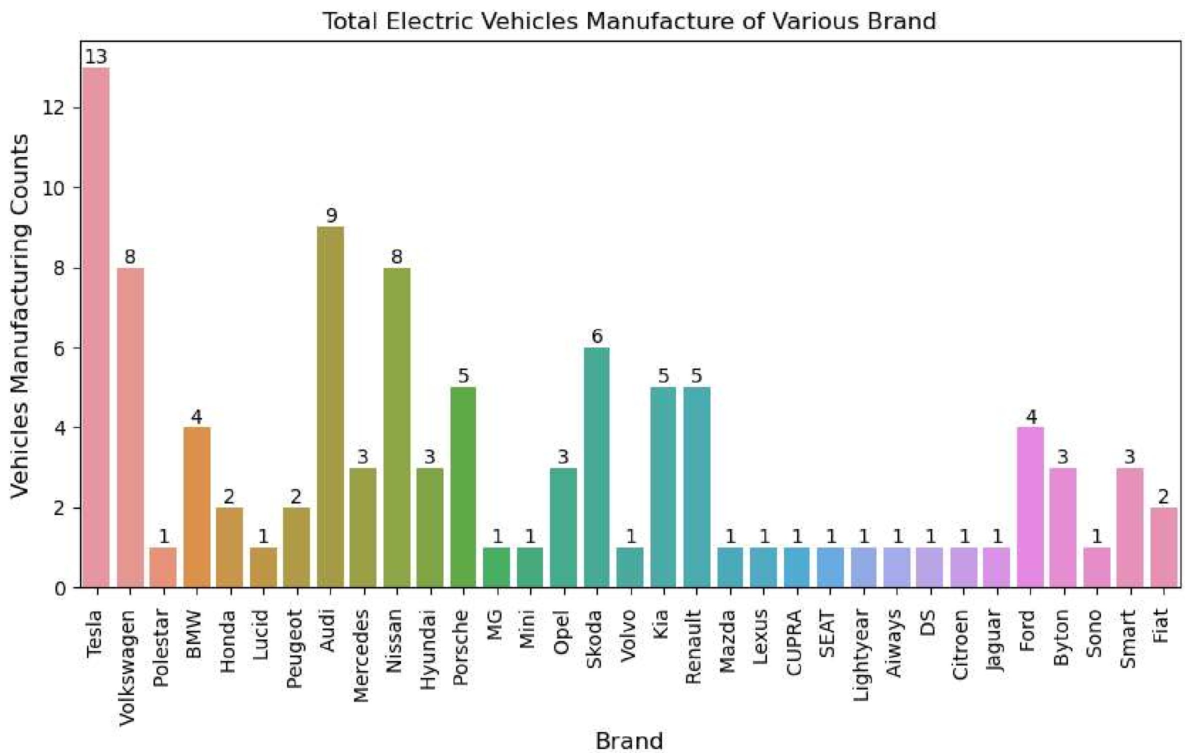

4.8
4.9
5.0
5.1
5.2
Seats


20000
40000
60000
80000
100000
PriceEuro

Visualisation

The most number of manufacturing vehicles

In [7]:
```
plt.figure(figsize=(10,5))
S=sns.countplot(data=df,x="Brand")
for v in S.containers:
    S.bar_label(v)
plt.title("Total Electric Vehicles Manufacture of Various Brand", size=12)
plt.xlabel("Brand", size=12)
plt.ylabel("Vehicles Manufacturing Counts", size=12)
plt.xticks(rotation=90)
plt.show()
```



Observation:

The chart shows the number of cars sold of different brands according to the dataset. It seems to be a bar chart with brand names on the x-axis and the number of cars model manufacturing on the y-axis.

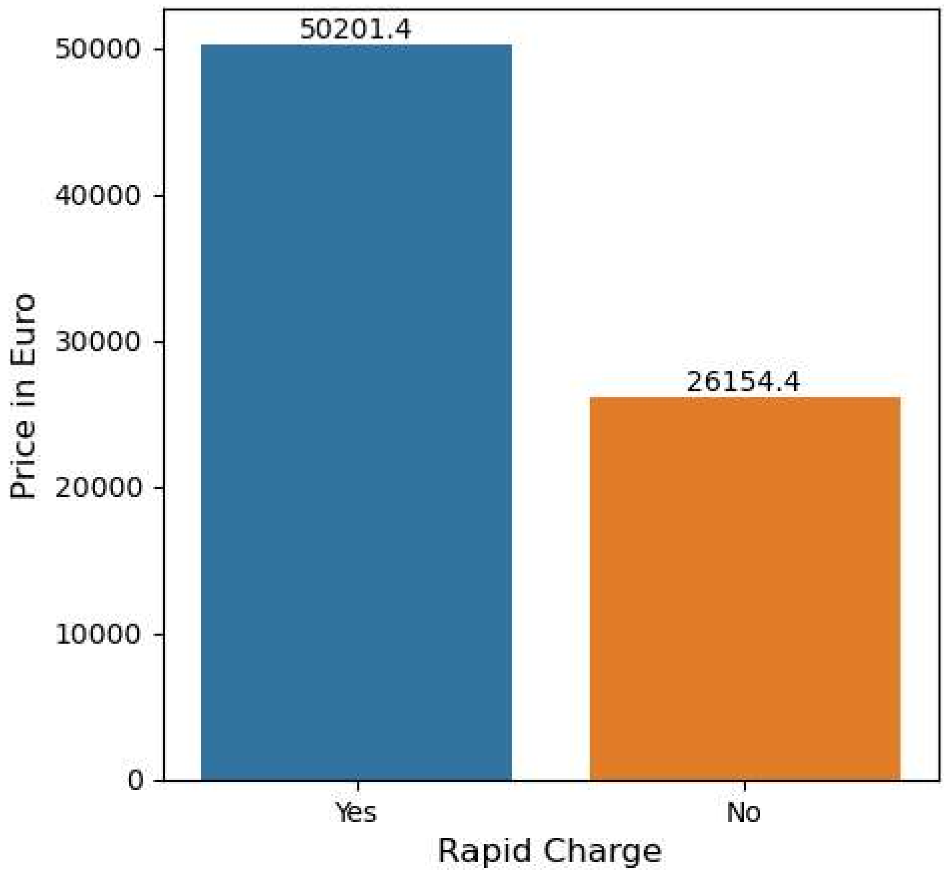
- Tesla has 13 models which is the highest quantity of vehicles.
- Audi is in the second position, with around 9 cars model manufacture.
- Volkswagem, Nissan and Skoda follow closely behind with around 8, 8 and 6 cars manufacture respectively.
- The number of cars model manufacture by other brands including Lucid, Peugeot, Ford, etc. are all fewer than 5.

Rapid charge

In [115]:
```
df["RapidCharge"].value_counts()
```

Out[115]:
```
RapidCharge
Yes    98
No      5
Name: count, dtype: int64
```

In [8]:
```
plt.figure(figsize=(5,5))
p=sns.barplot(data=df, x= "RapidCharge", y="PriceEuro", ci=False)
for v in p.containers:
    p.bar_label(v)
plt.xlabel("Rapid Charge", size=12)
plt.ylabel("Price in Euro", size=12)
plt.show()
```



Observation:

- graph shows the average price in Euros in Europe according to whether it has rapid charge or not. The y-axis shows the price in Euros and the x-axis shows rapid charge capability. There are two data points represented by bars. The blue bar on the left is labeled "No" for rapid charge and shows an average price of 26,154.4 Euros. The orange bar on the right is labeled "Yes" for rapid charge and shows an average price of 50,201.4 Euros.

Model Vehicles Acceleration

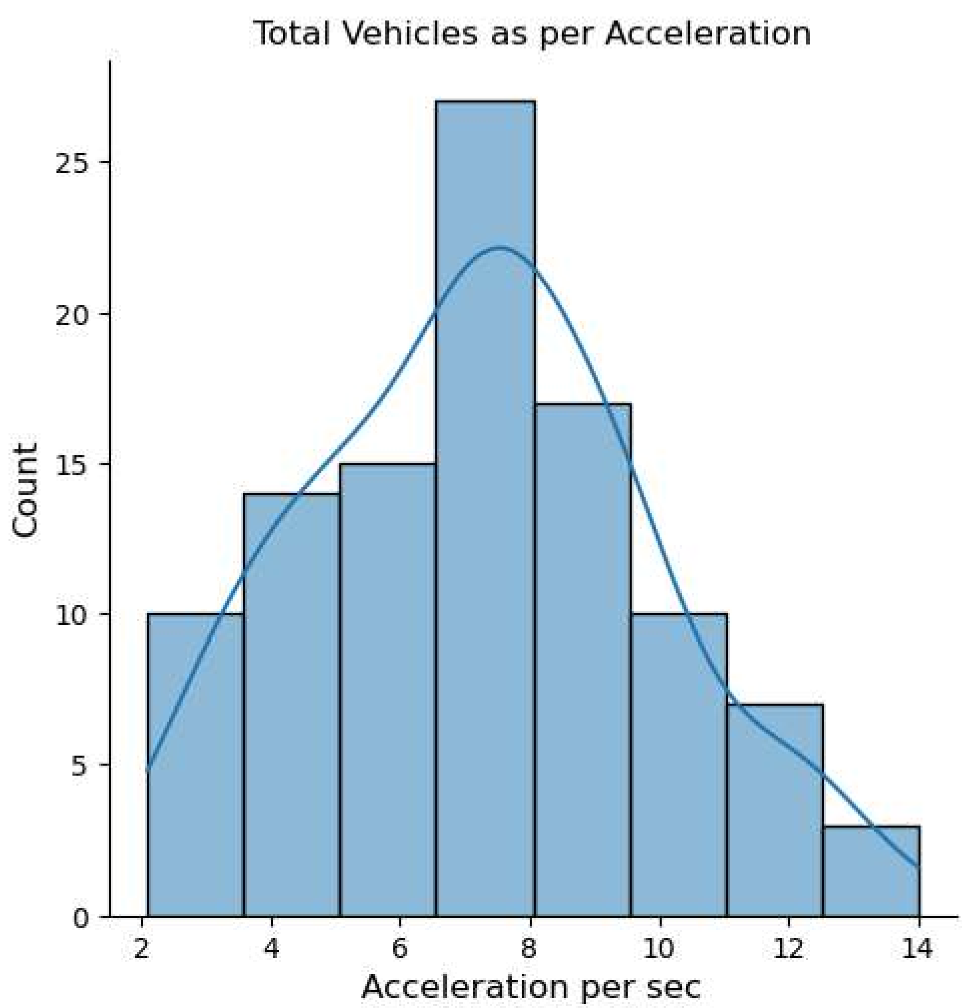
In [10]:
```
A=df.groupby(([["Brand", "Model"]), as_index=False)["AccelSec"].max().sort_value
A
```

Out[10]:

	Brand	Model	AccelSec
52	Nissan	e-NV200 Evalia	14.0
76	Smart	EQ forfour	12.7
65	Renault	Twingo ZE	12.6
70	Skoda	CITIGOe iV	12.3
69	SEAT	Mii Electric	12.3

In [9]:
```
plt.figure(figsize=(10,5))
sns.displot(data=df, x="AccelSec", kde=True)
plt.title("Total Vehicles as per Acceleration", size=12)
plt.xlabel("Acceleration per sec", size=12)
plt.ylabel("Count", size=12)
plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```



OBJECTIVES:

- Graph shows, The maximum range of cars as per acceleration is 6 to 8 per second.
- The count of manufacturing cars as per Acceleration per second incresing range from 2 to 8, after that decline the manufacturing cars range as highest acceleration per second.

Model vehicles efficiency

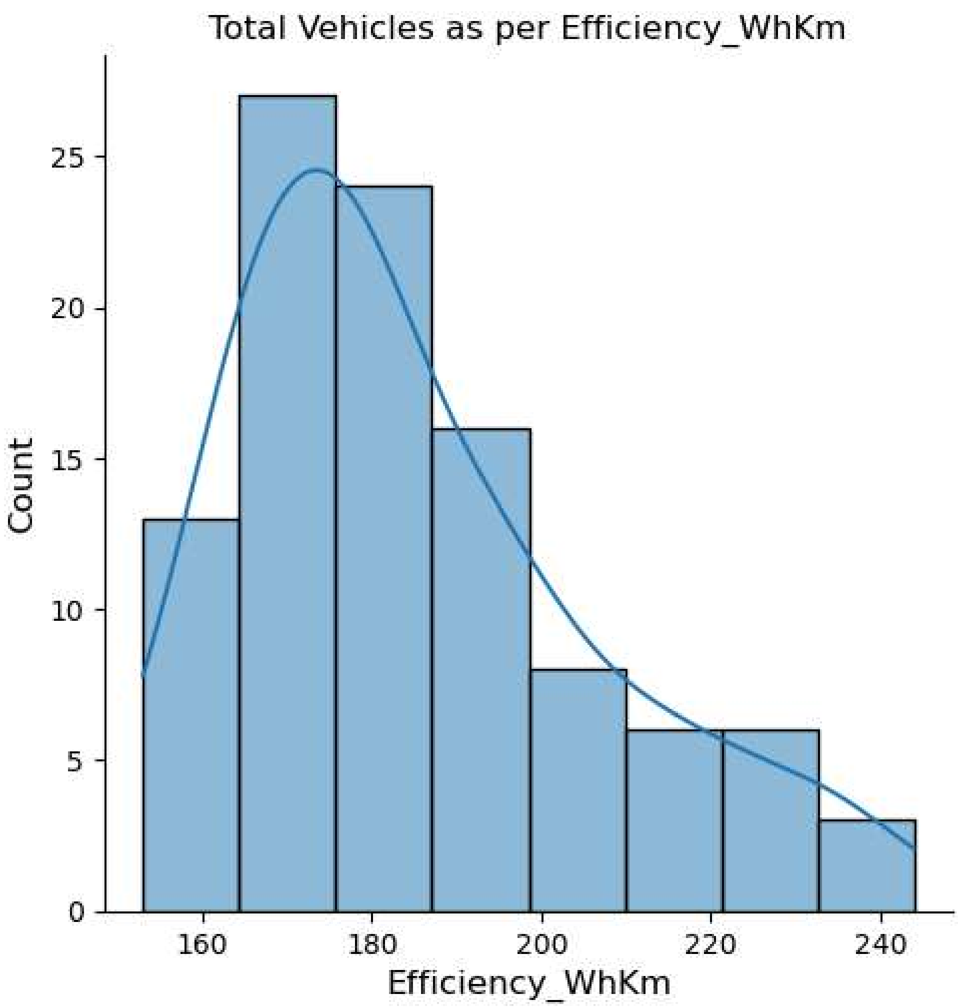
In [88]:
```
B=df.groupby((["Brand", "Model"]), as_index=False)["Efficiency_WhKm"].max().so
B
```

Out[88]:

	Brand	Model	Efficiency_WhKm
16	Byton	M-Byte 95 kWh 4WD	244
15	Byton	M-Byte 95 kWh 2WD	238
4	Audi	e-tron 55 quattro	237
31	Jaguar	I-Pace	232
49	Nissan	Ariya e-4ORCE 87kWh Performance	232

In [12]:
```
plt.figure(figsize=(10,5))
sns.displot(data=df, x="Efficiency_WhKm",kde=True)
plt.title("Total Vehicles as per Efficiency_WhKm", size=12)
plt.xlabel("Efficiency_WhKm", size=12)
plt.ylabel("Count", size=12)
plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```



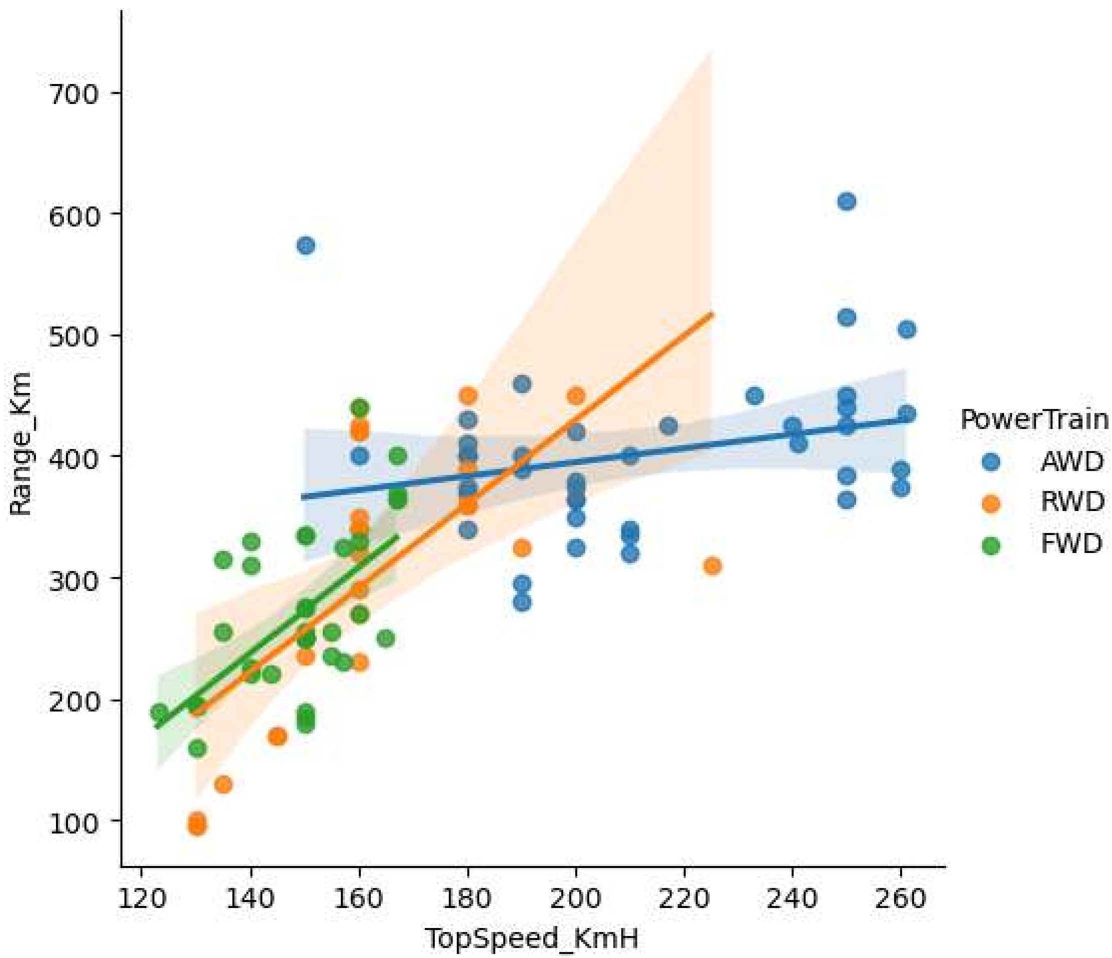
OBJECTIVES:

- Graph shows, car has the highest efficiency range from 150whkm to 175 whkm. afterthat, decline the graph of counts of cars as per highest efficiency range 180 onwards.

Relationship Range, Power Train and Top Speed

In [97]:
```
plt.figure(figsize=(5,5))
sns.lmplot(data=df,x="TopSpeed_KmH", y="Range_Km",hue="PowerTrain")
plt.title("Total Vehicles as per Efficiency_WhKm", size=12)
plt.xlabel("TopSpeed_KmH", size=12)
plt.ylabel("Range_Km", size=12)
plt.show()
```

```
<Figure size 500x500 with 0 Axes>
```

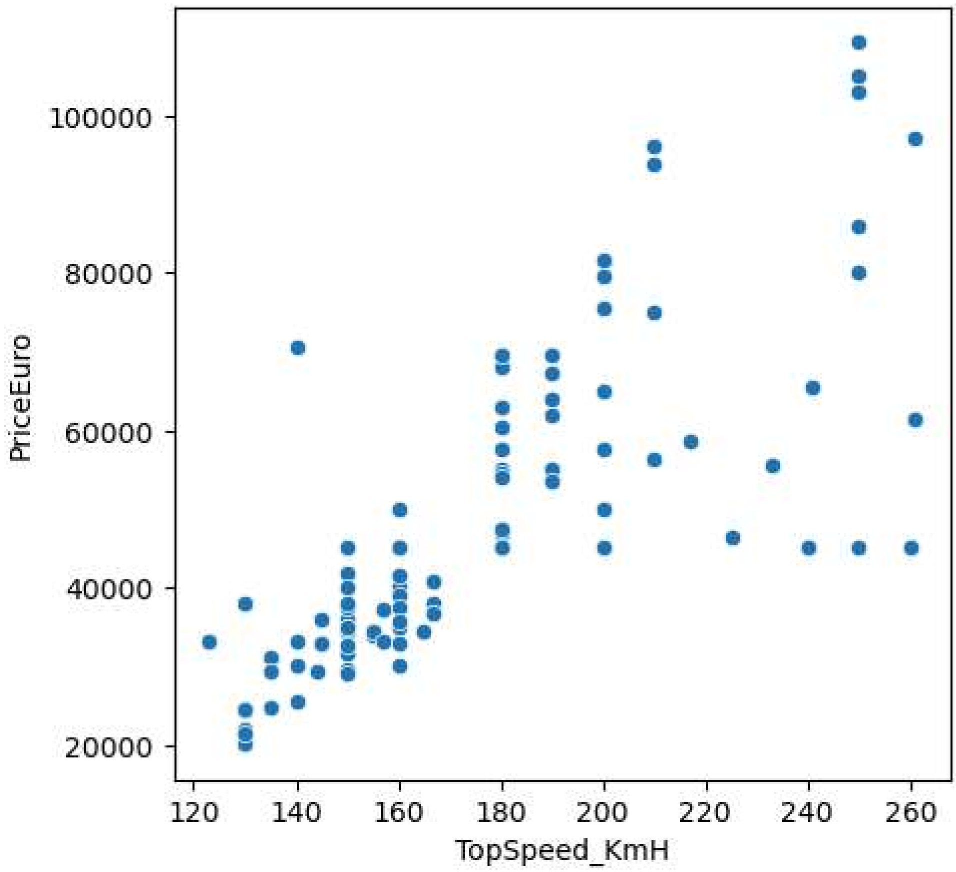


Observation:

- it appears to show a negative correlation between the top speed (TopSpeed_KmH) and the range (Range_Km) of a powertrain. This means that as the top speed of a powertrain increases, the range tends to decrease.

Car Price Depend on Top Speed

In [120]:
```
plt.figure(figsize=(5,5))
sns.scatterplot(data=df,x="TopSpeed_KmH", y="PriceEuro")
plt.show()
```



Observation:

- As per the graph shows, The top speed range from 120kmhr to 170kmhr maximum cars is available.
- As per top speed increase there car price in Euro also increase, but car model is specific.

In [121]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103 entries, 0 to 102
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Brand            103 non-null    object 
 1   Model            103 non-null    object 
 2   AccelSec         103 non-null    float64
 3   TopSpeed_KmH     103 non-null    int64  
 4   Range_Km         103 non-null    int64  
 5   Efficiency_WhKm  103 non-null    int64  
 6   FastCharge_KmH   103 non-null    object 
 7   RapidCharge      103 non-null    object 
 8   PowerTrain       103 non-null    object 
 9   PlugType         103 non-null    object 
 10  BodyStyle        103 non-null    object 
 11  Segment          103 non-null    object 
 12  Seats            103 non-null    int64  
 13  PriceEuro        103 non-null    int64  
dtypes: float64(1), int64(5), object(8)
memory usage: 11.4+ KB
```

LABEL ENCODING

In [193]:
```
from sklearn.preprocessing import LabelEncoder
```

In [194]:
```
LE=LabelEncoder()
LE
```

Out[194]:
```
LabelEncoder()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [195]:
```
def HCD(col):
 df[col]=LE.fit_transform(df[col])
```

In [196]:
```
for i in df.select_dtypes(include=['object',"int"]):
 HCD(i)
```

In [197]:
```
df.head()
```

Out[197]:

	Brand	Model	AccelSec	TopSpeed_KmH	Range_Km	Efficiency_WhKm	FastCharge_KmH	Ra
0	30	46	4.6	18	42	5	50	
1	31	33	10.0	9	15	9	7	
2	23	0	4.7	15	35	21	36	
3	2	101	6.8	12	28	32	32	
4	9	78	9.5	5	4	10	2	

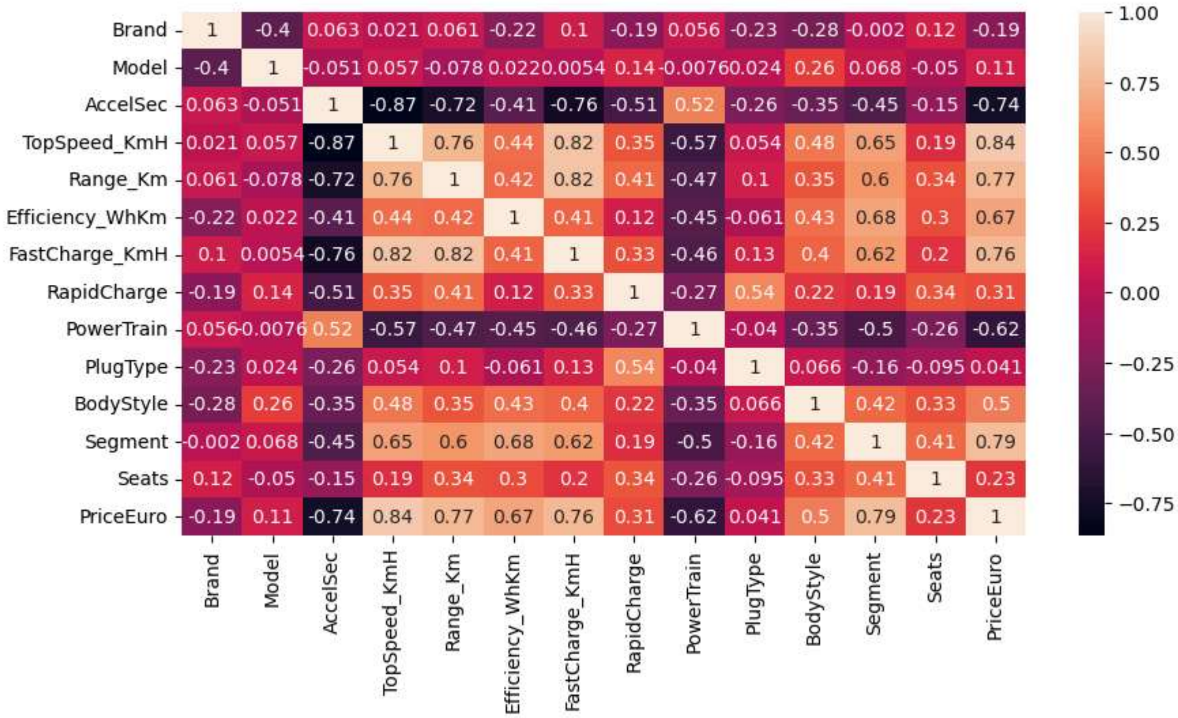
CO-RELATION

In [198]:
```
df.corr()
```

Out[198]:

	Brand	Model	AccelSec	TopSpeed_KmH	Range_Km	Efficiency_WhKm
Brand	1.000000	-0.401572	0.062730	0.021076	0.060537	-0.221659
Model	-0.401572	1.000000	-0.050635	0.057176	-0.077762	0.022491
AccelSec	0.062730	-0.050635	1.000000	-0.865154	-0.719853	-0.410615
TopSpeed_KmH	0.021076	0.057176	-0.865154	1.000000	0.756068	0.444486
Range_Km	0.060537	-0.077762	-0.719853	0.756068	1.000000	0.424530
Efficiency_WhKm	-0.221659	0.022491	-0.410615	0.444486	0.424530	1.000000
FastCharge_KmH	0.100688	0.005442	-0.759025	0.817411	0.821237	0.405366
RapidCharge	-0.188137	0.144293	-0.514820	0.349092	0.411901	0.116273
PowerTrain	0.056464	-0.007609	0.521011	-0.567529	-0.467350	-0.447413
PlugType	-0.231104	0.023750	-0.259657	0.054147	0.104279	-0.060855
BodyStyle	-0.275860	0.261255	-0.347164	0.477244	0.351384	0.433367
Segment	-0.002040	0.068414	-0.451568	0.650718	0.595759	0.679746
Seats	0.122233	-0.049640	-0.151456	0.189824	0.335400	0.302620
PriceEuro	-0.190202	0.111227	-0.744832	0.843350	0.768121	0.665857

In [199]:
```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



Observation:

- From the heatmep we can see that, there is strong correlation between **Segment** and **Bodystyle** to all columns

Dependent and independent Variable

In [200]:
```
X=df.drop('PriceEuro',axis=1)
Y=df['PriceEuro']
```

In [201]:
```
from sklearn.preprocessing import PowerTransformer
```

In [202]:
```
PT=PowerTransformer()
PT
```

Out[202]: PowerTransformer()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [203]:
```
X=PT.fit_transform(X)
X
```

Out[203]:
```
array([[ 1.11024277, -0.06511924, -0.96506971, ...,  1.15201559,
         0.36515734,  0.18486151],
       [ 1.19746121, -0.51080479,  0.92748087, ..., -1.23041849,
        -0.22999352,  0.18486151],
       [ 0.48983107, -2.06550802, -0.91934626, ..., -0.81233665,
         0.36515734,  0.18486151],
       ...,
       [ 0.21776396, -1.55298084, -0.41295663, ..., -1.23041849,
        -0.22999352,  0.18486151],
       [ 0.21776396, -1.4522779 , -0.74229179, ..., -1.23041849,
        -0.22999352,  0.18486151],
       [-1.45202334, -0.19814322,  0.16754078, ...,  0.7702779 ,
         0.87108961,  0.18486151]])
```

In [ ]:

Train Test Split

In [204]:
```
from sklearn.model_selection import train_test_split
```

In [205]:
```
x_train,x_test,y_train,y_test= train_test_split(X,Y,test_size=0.5,random_state=
```

LINEAR REGRESSION

In [206]:
```
from sklearn.linear_model import LinearRegression,Lasso,Ridge
```

In [207]:
```
LR=LinearRegression()
LR
```

Out[207]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [208]:
```
LR.fit(x_train,y_train)
```

Out[208]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [209]:
```
LR_pred=LR.predict(x_test)
LR_pred
```

Out[209]:
```
array([27.7175277 , 51.25101529, 19.58713409, 47.27647883, 66.2536085 ,
       42.33891015, 43.09444291, 25.13707989, 61.16030567, 33.68281546,
       -0.35116337, 35.06446839, 32.02280499, 48.50348134, 54.31717543,
       80.64085304, 57.9128585 ,  6.39416594, 24.9826461 , 14.57478702,
       33.72393862, 71.1680449 , 29.48496478,  8.85904758, 24.63402817,
       65.65849004, 37.39169826, 58.35888921, 24.7891184 , 20.50532928,
       88.1979006 , 28.27899562, 70.86744514, 75.72880439, 80.26247197,
       40.48666207, 35.91733351, 79.487313  , 31.03574896, 26.13597733,
       62.21423845, 19.51422183, 55.83713894, 25.99863622,  6.59745495,
       29.27105457,  9.07605316, 77.42660353, 40.49357554, 68.14652828,
       35.49191289, 35.03551446])
```

In [210]:
```
LR.score(x_train,y_train)
```

Out[210]:
```
0.9218577287049927
```

In [211]:
```
LR.score(x_test,y_test)
```

Out[211]:
```
0.8077838525012453
```

In [223]:
```
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

In [214]:
```
r2_score(y_test,LR_pred)
```

Out[214]:
```
0.8077838525012453
```

In [224]:
```
mean_squared_error(y_test,LR_pred)
```

Out[224]:
```
111.99000402231536
```

In [225]:
```
mean_absolute_error(y_test,LR_pred)
```

Out[225]:
```
6.86925832261604
```

Lasso

In [215]:
```
L1=Lasso(alpha=5)
L1
```

Out[215]:
```
Lasso(alpha=5)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [216]:
```
L1.fit(x_train,y_train)
```

Out[216]:
```
Lasso(alpha=5)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [217]:
```
L1_pred=L1.predict(x_test)
L1_pred
```

Out[217]:
```
array([37.64115418, 52.2304644 , 27.08492498, 47.50839039, 59.67521391,
       42.73763962, 48.25712095, 30.80366664, 60.35896435, 38.75676859,
       10.96336507, 39.05825869, 34.97818233, 52.44941462, 50.89404444,
       69.99374894, 52.44887237, 13.78704112, 28.77804631, 22.50410555,
       38.75676859, 62.89037864, 32.87986962, 18.81819835, 28.77804631,
       62.27859634, 41.4752325 , 53.06606836, 32.77930101, 26.82180539,
       77.09283312, 34.16461804, 64.12687063, 70.01720835, 70.4257721 ,
       42.49539371, 33.96167023, 70.6259343 , 35.31304375, 31.95374875,
       58.40385203, 25.44633505, 52.02226692, 34.84369376, 17.85935055,
       37.23191539, 13.78704112, 66.48407759, 41.7386019 , 60.04915878,
       40.92947394, 42.73763962])
```

In [218]:
```
L1.score(x_train,y_train)
```

Out[218]:
```
0.8440164280502673
```

In [219]:
```
L1.score(x_test,y_test)
```

Out[219]:
```
0.7297394737254546
```

In [220]:
```
from sklearn.metrics import r2_score
```

In [226]:
```
r2_score(y_test,L1_pred)
```

Out[226]:
```
0.7297394737254546
```

Ridge

In [227]:
```
L2=Ridge(alpha=10)
L2
```

Out[227]:
```
Ridge(alpha=10)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [228]:
```
L2.fit(x_train,y_train)
```

Out[228]:
```
Ridge(alpha=10)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [229]:
```
L2_pred=L2.predict(x_test)
L2_pred
```

Out[229]:
```
array([24.29089906, 55.55305501, 22.36916675, 50.61209234, 66.85219517,
       47.25437885, 42.41331688, 28.63634108, 62.42566025, 33.35926374,
        2.6694039 , 35.52115949, 38.18226964, 53.70673263, 50.40742583,
       75.31508684, 57.97963282,  6.90791678, 24.99133009, 17.06226909,
       33.37470879, 69.21593805, 26.37508052, 12.66281908, 24.33381809,
       62.69053013, 37.31474735, 58.05984987, 24.74900673, 17.62234515,
       82.68739696, 28.01774783, 70.62960524, 72.53282196, 76.22430741,
       39.65527271, 35.68802964, 77.10410142, 30.21606963, 29.45039659,
       60.80309853, 19.06011503, 54.93125752, 22.87870072, 10.28267111,
       29.92808621,  8.44918362, 74.83644134, 42.61821592, 64.18478645,
       32.07294782, 32.19496363])
```

In [230]:
```
L2.score(x_train,y_train)
```

Out[230]:
```
0.9142114894771458
```

In [231]:
```
L2.score(x_test,y_test)
```

Out[231]:
```
0.8301930198993684
```

In [232]:
```
from sklearn.metrics import r2_score
```

In [233]:
```
r2_score(y_test,L2_pred)
```

Out[233]:
```
0.8301930198993684
```

RANDOM FOREST REGRESSION

In [234]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [235]:
```
DTR=RandomForestRegressor(n_estimators=200, random_state=0)
```

In [236]:
```
DTR.fit(x_train,y_train)
```

Out[236]:
```
RandomForestRegressor(n_estimators=200, random_state=0)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [237]:
```
model_pred=DTR.predict(x_test)
model_pred[:5]
```

Out[237]:
```
array([19.37 , 56.88 , 20.2  , 51.205, 65.775])
```

In [238]:
```
y_test[:5]
```

Out[238]:
```
1     11
0     52
20     8
88    46
42    72
Name: PriceEuro, dtype: int64
```

In [239]:
```
DTR.score(x_train,y_train)
```

Out[239]:
```
0.9787455656324582
```

In [240]:
```
DTR.score(x_test,y_test)
```

Out[240]:
```
0.8373312883747117
```

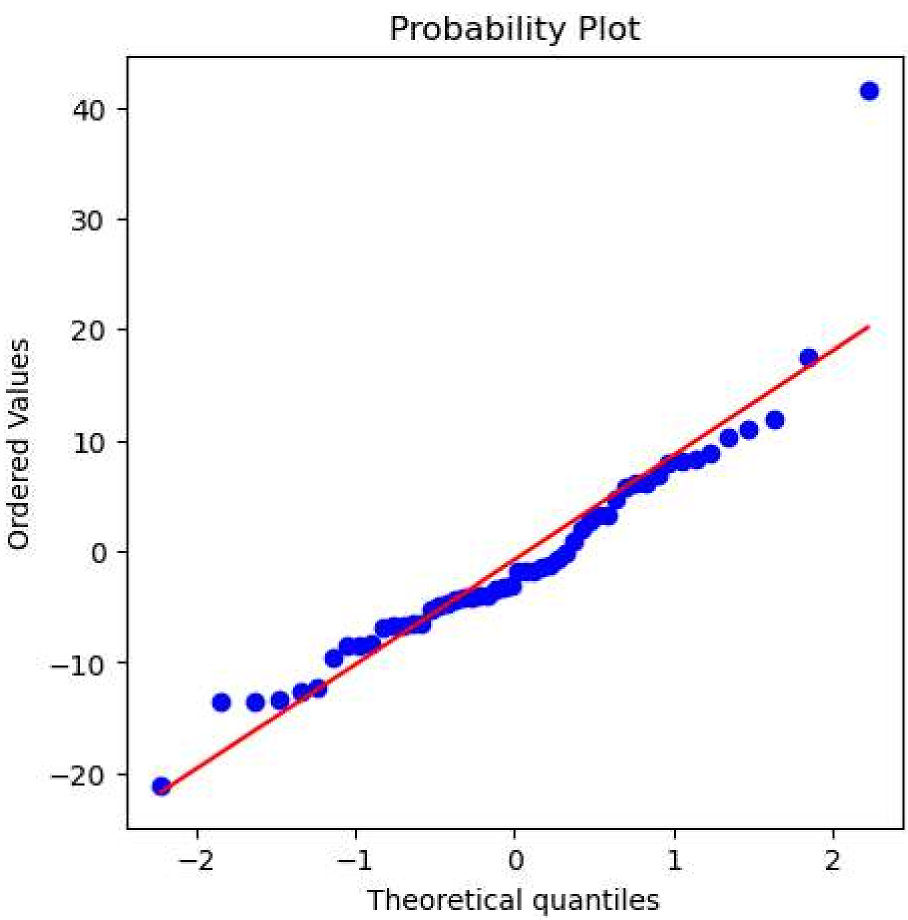
In [241]:
```
from sklearn.metrics import r2_score
```

In [242]:
```
r2_score(y_test,model_pred)
```

Out[242]:
```
0.8373312883747117
```

In [244]:
```
import scipy as sp
```

In [246]:
```
test_res=y_test-model_pred
fig,ax=plt.subplots(figsize=(5,5))
prediction=sp.stats.probplot(test_res,plot=ax)
```



- as per the graph, **Actual values** is on the **Prediction line** that is **Errors** between Actual valus and Prediction line is remove by using Random forest regression.
- Actual values is on the Prediction line, our **prediction** is **good**.

Conclusion:

In conclusion, factors such as performance, range, charging infrastructure, and price play significant roles in influencing electric car selection for potential buyers. The decision ultimately depends on individual preferences, priorities, and budget constraints.

In [ ]: