Data Preprocessing

In [167]:

```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from pandas.plotting import scatter_matrix
import statsmodels.api as sm

from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler

import tensorflow
from keras.models import Sequential
from keras.layers import Dense
```

In [31]:

```
# Importing the dataset
df = pd.read_csv('data.csv')
```

In [32]:

```
df
```

Out[32]:

	ActualPower	Max Capacity	Location 1	Location 2	Location 4	Location 5
0	3.724	45.0	5.5	9.138	9.828	7.346
1	3.424	45.0	4.9	9.038	9.736	7.594
2	3.994	45.0	4.3	8.977	9.613	7.712
3	6.813	45.0	4.0	8.921	9.446	7.731
4	7.737	45.0	5.1	8.811	9.244	7.716
...	...	...	...	...	...	...
333	25.258	45.0	7.2	6.706	6.862	3.250
334	21.316	45.0	8.3	6.776	6.900	3.072
335	18.691	45.0	7.5	6.675	6.891	3.056
336	20.694	45.0	7.6	6.431	6.841	3.189
337	18.832	45.0	8.9	6.049	6.694	3.322

338 rows × 6 columns

In [33]:

```
df.describe()
```

Out[33]:

	ActualPower	Max Capacity	Location 1	Location 2	Location 4	Location 5
count	338.000000	338.000000	337.000000	336.000000	338.000000	337.000000
mean	20.042633	44.729290	7.918694	9.539271	9.412246	6.669478
std	13.184409	0.577727	3.078309	4.217089	4.085693	2.780405
min	0.039000	43.500000	0.400000	0.495000	0.458000	0.481000
25%	6.807000	45.000000	5.500000	6.219500	6.496500	4.661000
50%	23.230000	45.000000	7.800000	9.088000	9.031500	6.556000
75%	31.861000	45.000000	10.400000	12.577250	12.258000	8.229000
max	41.163000	45.000000	16.200000	17.922000	17.665000	12.354000

In [34]:

```
# Let's check how much the data are spread out from the mean.
mean_ActualPower = np.mean(df['ActualPower'], axis=0)
sd_ActualPower = np.std(df['ActualPower'], axis=0)

mean_MaxCapacity = np.mean(df['Max Capacity'], axis=0)
sd_MaxCapacity = np.std(df['Max Capacity'], axis=0)

mean_Location1 = np.mean(df['Location 1'], axis=0)
sd_Location1 = np.std(df['Location 1'], axis=0)

mean_Location2 = np.mean(df['Location 2'], axis=0)
sd_Location2 = np.std(df['Location 2'], axis=0)

mean_Location4 = np.mean(df['Location 4'], axis=0)
sd_Location4 = np.std(df['Location 4'], axis=0)

mean_Location5 = np.mean(df['Location 5'], axis=0)
sd_Location5 = np.std(df['Location 5'], axis=0)

counter_actual_power = 0
counter_maxcapacity = 0
counter_loc1 = 0
counter_loc2 = 0
counter_loc4 = 0
counter_loc5 = 0

for actual_power, maxcapacity, loc1, loc2, loc4, loc5 in zip(df['ActualPower'], df
['Max Capacity'], df['Location 1'], df['Location 2'], df['Location 4'], df['Locati
on 5']):
    if not mean_ActualPower - 3*sd_ActualPower <= actual_power <= mean_ActualPower
+ 3*sd_ActualPower:
        counter_actual_power += 1
    if not mean_MaxCapacity - 3*sd_MaxCapacity <= maxcapacity <= mean_MaxCapacity
+ 3*sd_MaxCapacity:
        counter_maxcapacity += 1
    if not mean_Location1 - 3*sd_Location1 <= counter_loc1 <= mean_Location1 + 3*s
d_Location1:
        counter_loc1 += 1
    if not mean_Location2 - 3*sd_Location2 <= counter_loc2 <= mean_Location2 + 3*s
d_Location2:
        counter_loc2 += 1
    if not mean_Location4 - 3*sd_Location4 <= counter_loc4 <= mean_Location4 + 3*s
d_Location4:
        counter_loc4 += 1
    if not mean_Location5 - 3*sd_Location5 <= counter_loc5 <= mean_Location5 + 3*s
d_Location5:
        counter_loc5 += 1

counter_dicts = {'counter_actual_power': counter_actual_power,
                'counter_maxcapacity': counter_maxcapacity,
                'counter_loc1': counter_loc1,
                'counter_loc2': counter_loc2,
                'counter_loc4': counter_loc4,
                'counter_loc5': counter_loc5}
print(counter_dicts)
```

```
{'counter_actual_power': 0, 'counter_maxcapacity': 0, 'counter_loc1':
0, 'counter_loc2': 0, 'counter_loc4': 0, 'counter_loc5': 0}
```

Как мы видим, ни для одной из переменных нет значений которые меньше, чем mean - 3 * std.

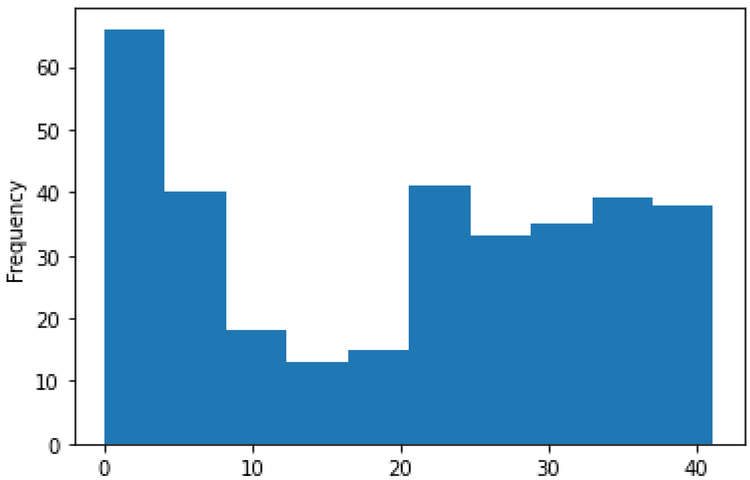
Построим гистограммы для того, чтобы посмотреть, как распределяется каждая переменная.

In [12]:

```
# ActualPower distribution
df['ActualPower'].plot(kind = 'hist')
```

Out[12]:

```
<AxesSubplot:ylabel='Frequency'>
```

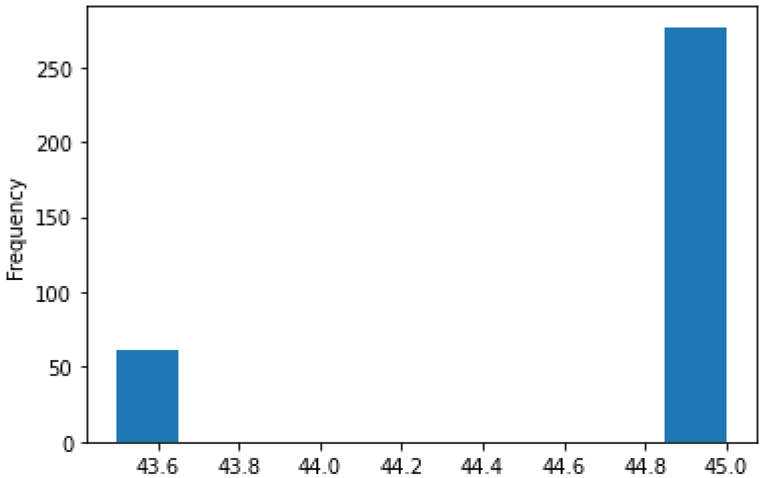


In [13]:

```
# Max Capacity distribution
df['Max Capacity'].plot(kind = 'hist')
```

Out[13]:

<AxesSubplot:ylabel='Frequency'>

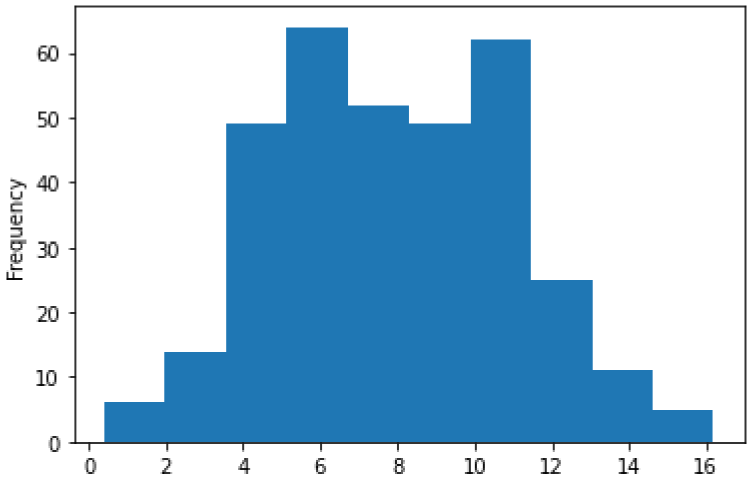


In [14]:

```
# Location 1 distribution
df['Location 1'].plot(kind = 'hist')
```

Out[14]:

<AxesSubplot:ylabel='Frequency'>

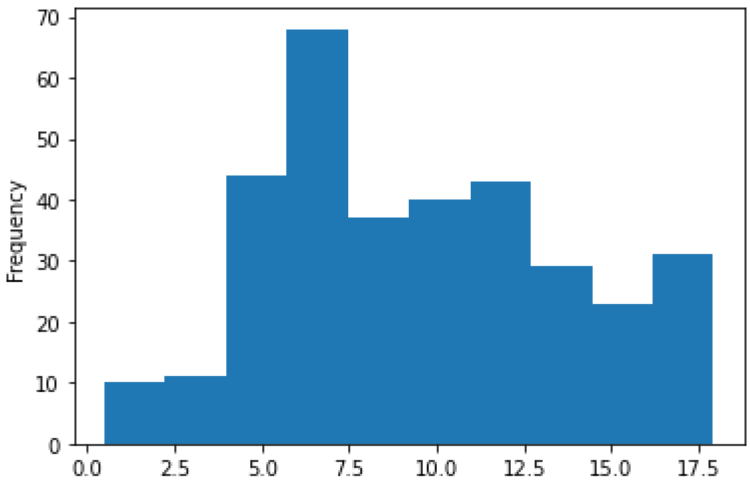


In [15]:

```
# Location 2 distribution
df['Location 2'].plot(kind = 'hist')
```

Out[15]:

<AxesSubplot:ylabel='Frequency'>

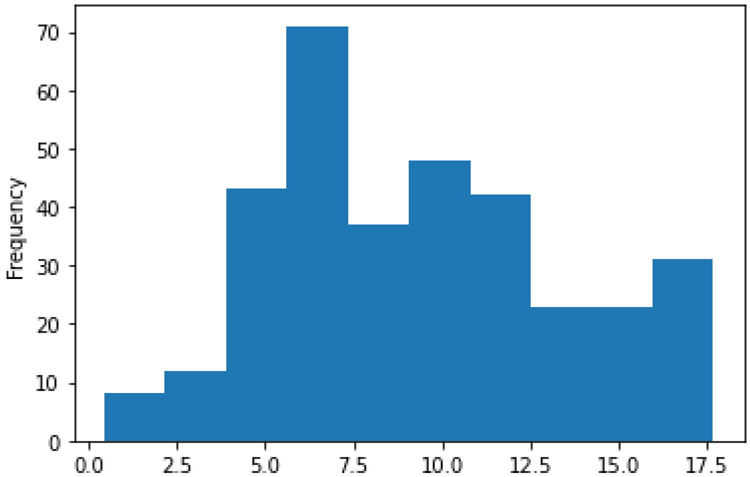


In [16]:

```
# Location 4 distribution
df['Location 4'].plot(kind = 'hist')
```

Out[16]:

```
<AxesSubplot:ylabel='Frequency'>
```

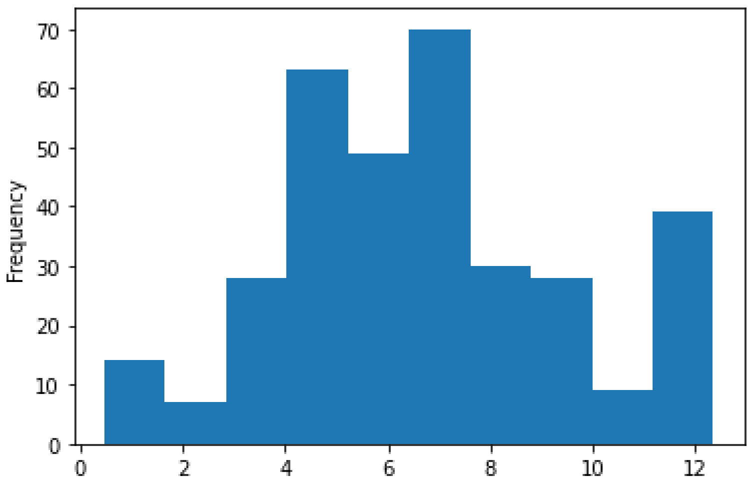


In [17]:

```
# Location 5 distribution
df['Location 5'].plot(kind = 'hist')
```

Out[17]:

<AxesSubplot:ylabel='Frequency'>



Так как все данные являются относительно симметричными мы не будем использовать логарифмирование.

Проверим пропущенные данные в колонках.

In [35]:

```
df.isnull().sum()
# Таким образом мы имеем пропущенные значения в таких колонках:
```

Out[35]:

```
ActualPower     0
Max Capacity    0
Location 1      1
Location 2      2
Location 4      0
Location 5      1
dtype: int64
```

Избавимся от пропущенных данных в колонках путем их замены на среднее значение в колонке.

In [36]:

```
#Deal with missing data
#numeric
df[['Location 1']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_tra
nsform(df[['Location 1']]).round()
df[['Location 2']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_tra
nsform(df[['Location 2']]).round()
df[['Location 5']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_tra
nsform(df[['Location 5']]).round()
```

In [37]:

```
df.isnull().sum()
```

Out[37]:

```
ActualPower     0
Max Capacity    0
Location 1      0
Location 2      0
Location 4      0
Location 5      0
dtype: int64
```

Linear Regression

In [38]:

```
# Cheking correlations
correlation = df.corr()
correlation.style.background_gradient(cmap='coolwarm')
```

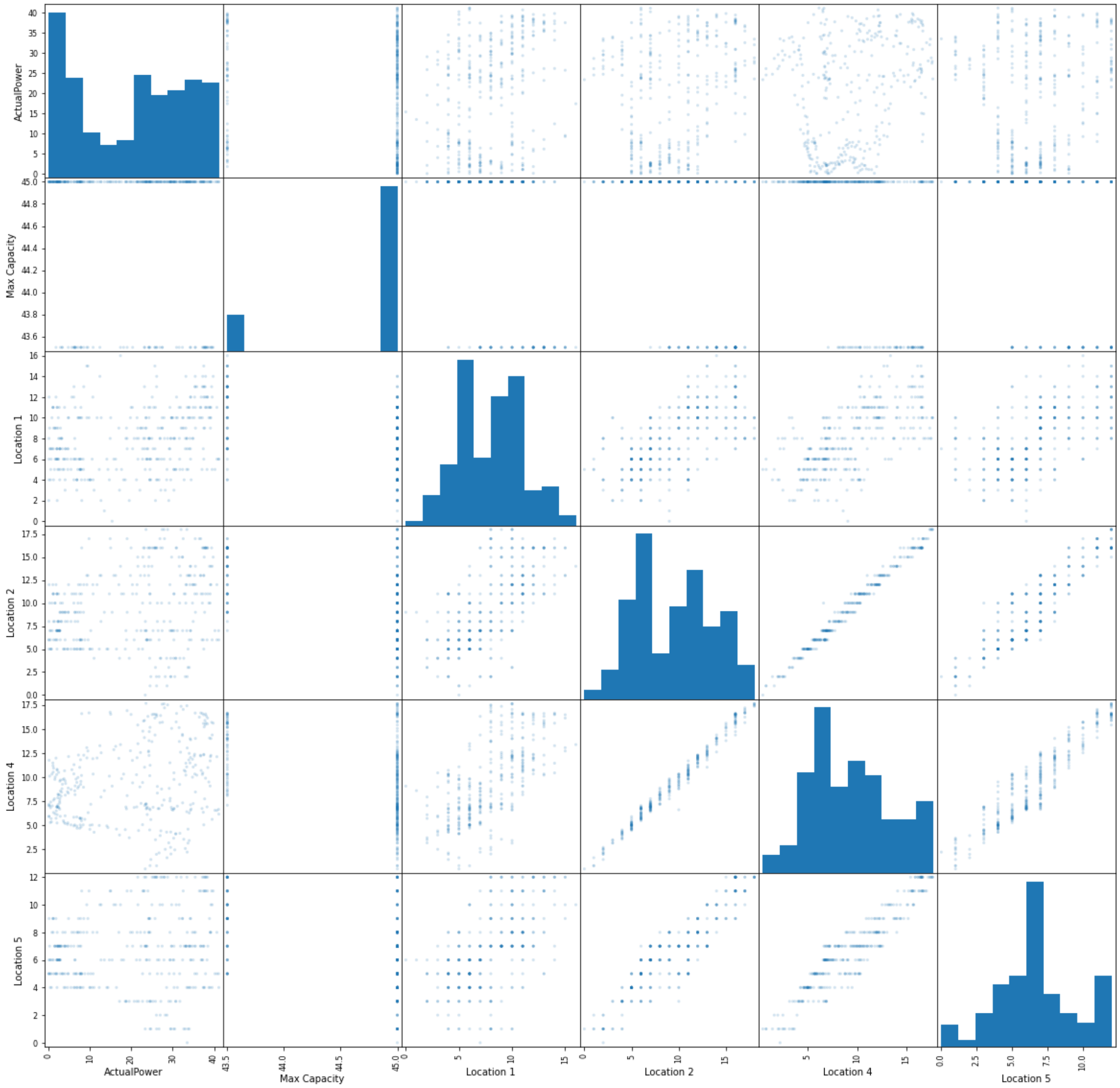
Out[38]:

	ActualPower	Max Capacity	Location 1	Location 2	Location 4	Location 5
ActualPower	1.000000	-0.099136	0.297014	0.268269	0.256173	0.113401
Max Capacity	-0.099136	1.000000	-0.429784	-0.429683	-0.422071	-0.398832
Location 1	0.297014	-0.429784	1.000000	0.639311	0.648041	0.580977
Location 2	0.268269	-0.429683	0.639311	1.000000	0.992052	0.911672
Location 4	0.256173	-0.422071	0.648041	0.992052	1.000000	0.937005
Location 5	0.113401	-0.398832	0.580977	0.911672	0.937005	1.000000

Как мы видим, корреляция с y(ActualPower) дл всех переменных не прывышает 0.3. Зависимость с Max Capacity - обратная.

In [39]:

```
scatter_matrix(df, alpha=0.2, figsize=(20, 20))
plt.show()
```


ActualPower
Max Capacity
Location 1
Location 2
Location 4
Location 5

Simple Linear Regression

Построим линейную регрессию с Location 1 в качестве X (так как наиболее высокое значение корреляции - 0,297).

In [40]:

```
# Splitting the dataset into the Training set and Test set
X = df.iloc[:, 1:6].values
y = df.iloc[:, 0].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_st
ate=0)
```

In [41]:

```
# Fitting Simple Linear Regression to the Training set (Location 1)
from sklearn.linear_model import LinearRegression
sr = LinearRegression().fit(X_train[:, 1:2], y_train)
```

In [42]:

```
# Getting parameters
sr.coef_, sr.intercept_
```

Out[42]:

```
(array([1.15783522]), 10.495204358568708)
```

In [43]:

```
# Predicting the Test set results
y_pred = sr.predict(X_test[:, 1:2])
```

In [44]:

```
# Coefficient of determination R^2
sr.score(X_train[:, 1:2], y_train), sr.score(X_test[:, 1:2], y_test)
```

Out[44]:

```
(0.07261775301646012, 0.1219538083093914)
```

Исходя из R^2 делаем вывод, что модель неадеватна и ее нельзя использовать для прогнозирования.

In [45]:

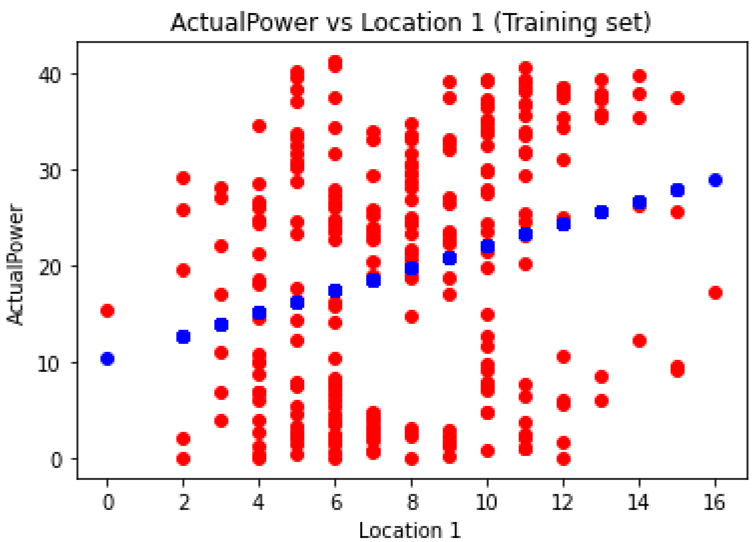
```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, sr.predict(X_train[:, 1:2])), mean_squared_error(y_tes
t, y_pred)
```

Out[45]:

```
(162.24736726069074, 142.79267630376148)
```

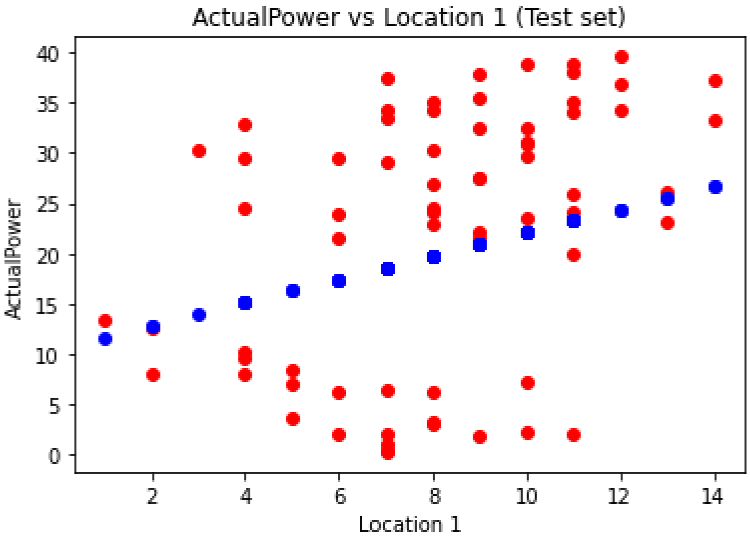
In [46]:

```
# Visualising the Training set results
plt.scatter(X_train[:,1], y_train, color = 'red')
plt.plot(X_train[:,1], sr.predict(X_train[:, 1:2]), 'bo')
plt.title('ActualPower vs Location 1 (Training set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



In [47]:

```
# Visualising the Test set results
plt.scatter(X_test[:,1], y_test, color = 'red')
plt.plot(X_test[:,1], sr.predict(X_test[:, 1:2]), 'bo')
plt.title('ActualPower vs Location 1 (Test set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



Multiple Linear Regression

А теперь попробуем построить линейную регрессию используя все переменные.

In [48]:

```
# Fitting Multiple Linear Regression to the Training set
mr = LinearRegression().fit(X_train, y_train)
```

In [49]:

```
# Getting parameters
mr.coef_, mr.intercept_
```

Out[49]:

```
(array([ 0.75281641,  0.76395725, -1.03390464,  4.474406  , -4.6146765
2]),
 -21.33907698323824)
```

In [50]:

```
# Predicting the Test set results
y_pred = mr.predict(X_test)
```

In [51]:

```
# Coefficient of determination R^2
mr.score(X_train, y_train), mr.score(X_test, y_test)
```

Out[51]:

```
(0.17953060354674233, 0.3550212373146102)
```

По сравнению с линейной регрессией одной переменной (0.07261775301646012, 0.1219538083093914) показатели R^2 улучились, но незначительно. Модель всё еще не пригодна для прогноза.

In [52]:

```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, mr.predict(X_train)), mean_squared_error(y_test, y_pre
d)
```

Out[52]:

```
(143.54275157358248, 104.88997566928406)
```

In [53]:

```
# p-values
X = sm.add_constant(X_train)
mr1 = sm.OLS(y_train, X).fit()
mr1.pvalues
```

Out[53]:

```
array([7.54687317e-01, 6.15698513e-01, 2.52691593e-02, 4.92236208e-01,
       1.53921880e-02, 1.20044195e-07])
```

In [54]:

```
mr1.summary()
```

Out[54]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.180
Model:	OLS	**Adj. R-squared:**	0.164
Method:	Least Squares	**F-statistic:**	11.55
Date:	Thu, 08 Oct 2020	**Prob (F-statistic):**	4.20e-10
Time:	22:08:08	**Log-Likelihood:**	-1053.6
No. Observations:	270	**AIC:**	2119.
Df Residuals:	264	**BIC:**	2141.
Df Model:	5		
Covariance Type:	nonrobust		

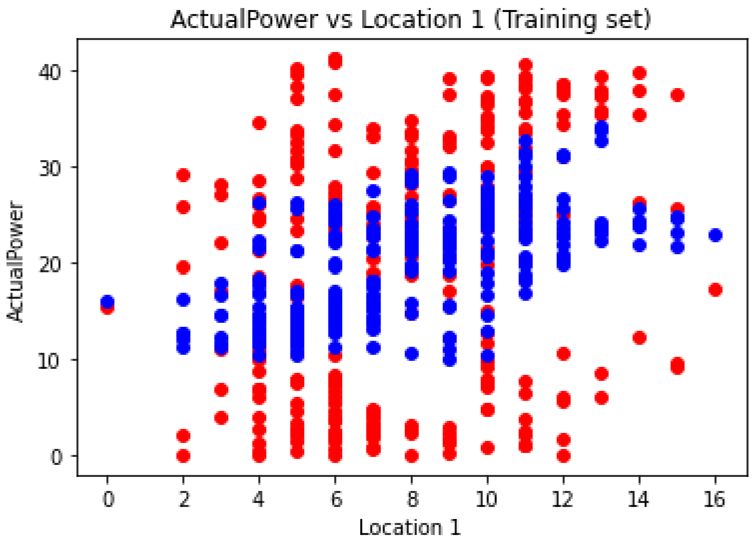
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-21.3391	68.222	-0.313	0.755	-155.667	112.989
x1	0.7528	1.498	0.503	0.616	-2.197	3.702
x2	0.7640	0.340	2.250	0.025	0.095	1.432
x3	-1.0339	1.503	-0.688	0.492	-3.994	1.926
x4	4.4744	1.835	2.439	0.015	0.862	8.087
x5	-4.6147	0.848	-5.442	0.000	-6.284	-2.945

Omnibus:	84.474	**Durbin-Watson:**	1.851
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	13.922
Skew:	0.037	**Prob(JB):**	0.000948
Kurtosis:	1.890	**Cond. No.**	4.42e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.42e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

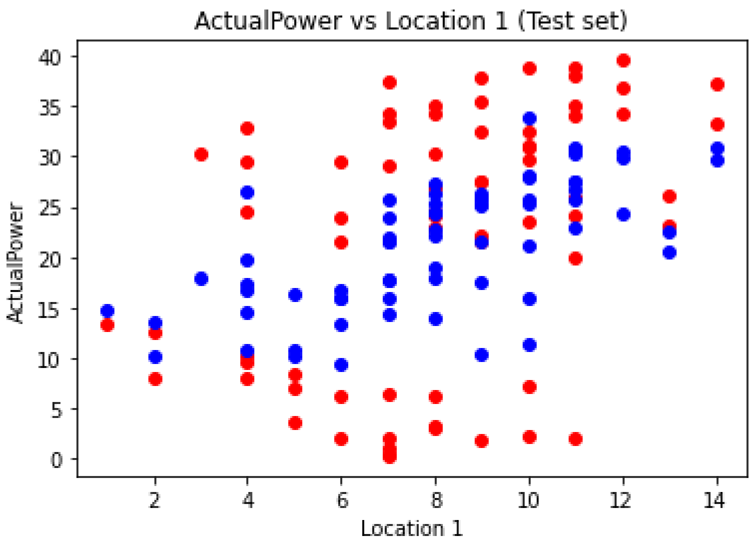
In [55]:

```
# Visualising the Training set results
plt.scatter(X_train[:,1], y_train, color = 'red')
plt.plot(X_train[:,1], mr.predict(X_train), 'bo')
plt.title('ActualPower vs Location 1 (Training set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



In [56]:

```
# Visualising the Test set results
plt.scatter(X_test[:,1], y_test, color = 'red')
plt.plot(X_test[:,1], mr.predict(X_test), 'bo')
plt.title('ActualPower vs Location 1 (Test set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



Polynomial Regression

Построим полиномиальную регрессию.

In [57]:

```
# Fitting Polynomial Regression to the dataset
from sklearn.preprocessing import PolynomialFeatures
X_train_p = PolynomialFeatures().fit_transform(X_train[:, 1:2])
X_test_p = PolynomialFeatures().fit_transform(X_test[:, 1:2])
pr = LinearRegression().fit(X_train_p[:,1:], y_train)
```

In [58]:

```
# Getting parameters
pr.coef_, pr.intercept_
```

Out[58]:

```
(array([0.58821149, 0.03456267]), 12.509313919229896)
```

In [59]:

```
# Predicting the Test set results
y_pred = pr.predict(X_test_p[:,1:])
```

In [60]:

```
# Coefficient of determination R^2
pr.score(X_train_p[:,1:], y_train), pr.score(X_test_p[:,1:], y_test)
```

Out[60]:

```
(0.07342643910197744, 0.12402707185119399)
```

Исходя из R^2 делаем вывод, что модель неадеватна и ее нельзя использовать для прогнозирования.

In [61]:

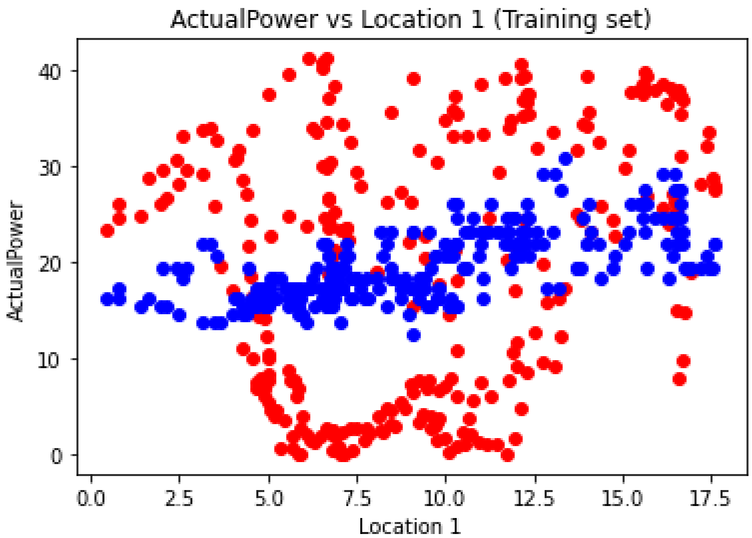
```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, pr.predict(X_train_p[:,1:])), mean_squared_error(y_tes
t, y_pred)
```

Out[61]:

```
(162.10588602278446, 142.45551084183177)
```

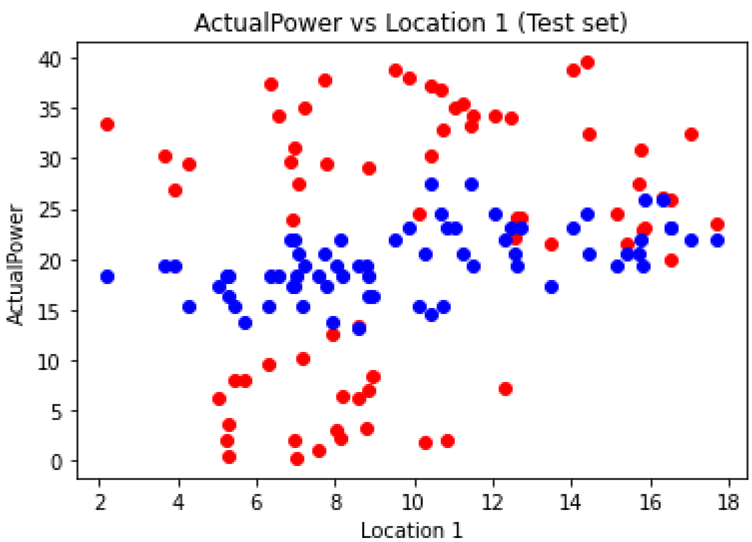
In [64]:

```
# Visualising the Training set results
plt.scatter(X_train[:,3], y_train, color = 'red')
plt.plot(X_train[:,3], pr.predict(X_train_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 1 (Training set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



In [65]:

```
# Visualising the Test set results
plt.scatter(X_test[:,3], y_test, color = 'red')
plt.plot(X_test[:,3], pr.predict(X_test_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 1 (Test set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



Попробуем сделать полиномиальную модель с другими переменными.

In [73]:

```
# MAX CAPACITY
# Fitting Polynomial Regression to the dataset
from sklearn.preprocessing import PolynomialFeatures
X_train_p = PolynomialFeatures().fit_transform(X_train[:, 0:1])
X_test_p = PolynomialFeatures().fit_transform(X_test[:, 0:1])
pr = LinearRegression().fit(X_train_p[:,1:], y_train)
```

In [74]:

```
# Getting parameters
pr.coef_, pr.intercept_
```

Out[74]:

```
(array([-0.00032473, -0.02873888]), 77.10044660556888)
```

In [75]:

```
# Predicting the Test set results
y_pred = pr.predict(X_test_p[:,1:])

# Coefficient of determination R^2
pr.score(X_train_p[:,1:], y_train), pr.score(X_test_p[:,1:], y_test)
```

Out[75]:

```
(0.012361222860595933, -0.0338804583810739)
```

Исходя из R^2 делаем вывод, что модель неадеватна и ее нельзя использовать для прогнозирования.

In [76]:

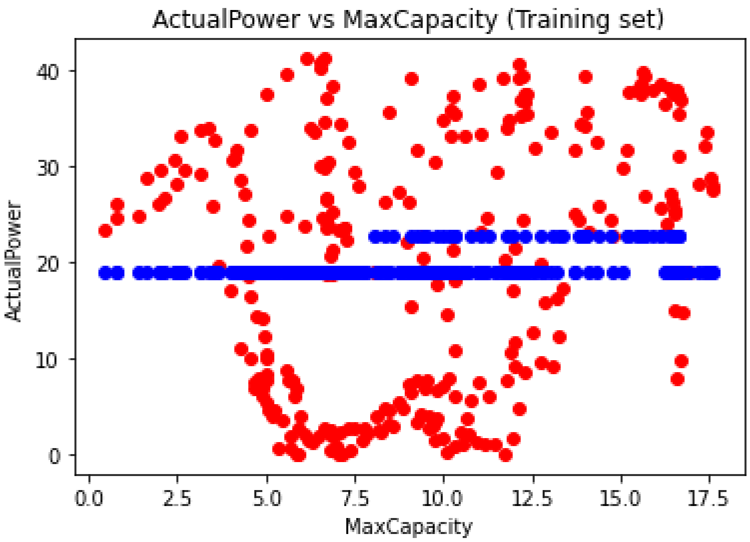
```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, pr.predict(X_train_p[:,1:])), mean_squared_error(y_tes
t, y_pred)
```

Out[76]:

```
(172.78936696992918, 168.13529746782712)
```

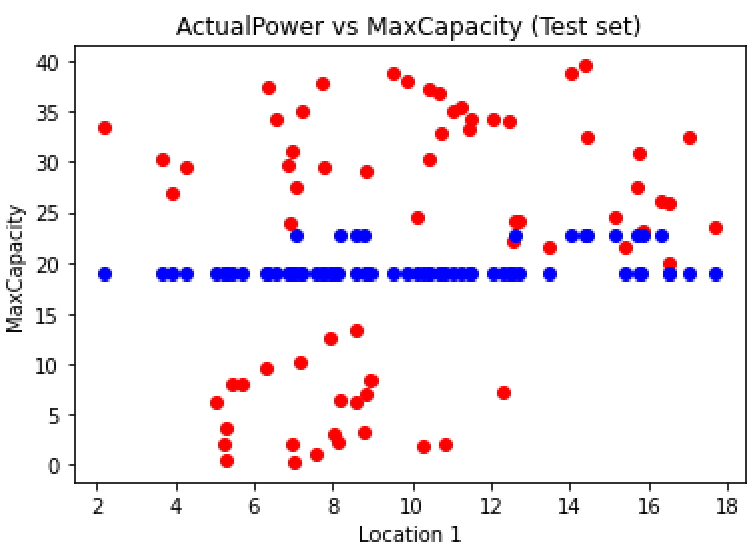
In [77]:

```
# Visualising the Training set results
plt.scatter(X_train[:,3], y_train, color = 'red')
plt.plot(X_train[:,3], pr.predict(X_train_p[:,1:]), 'bo')
plt.title('ActualPower vs MaxCapacity (Training set)')
plt.xlabel('MaxCapacity')
plt.ylabel('ActualPower')
plt.show()
```



In [78]:

```
# Visualising the Test set results
plt.scatter(X_test[:,3], y_test, color = 'red')
plt.plot(X_test[:,3], pr.predict(X_test_p[:,1:]), 'bo')
plt.title('ActualPower vs MaxCapacity (Test set)')
plt.xlabel('Location 1')
plt.ylabel('MaxCapacity')
plt.show()
```



In [79]:

```
# LOCATION 2
# Fitting Polynomial Regression to the dataset
from sklearn.preprocessing import PolynomialFeatures
X_train_p = PolynomialFeatures().fit_transform(X_train[:, 2:3])
X_test_p = PolynomialFeatures().fit_transform(X_test[:, 2:3])
pr = LinearRegression().fit(X_train_p[:,1:], y_train)
```

In [80]:

```
# Getting parameters
pr.coef_, pr.intercept_
```

Out[80]:

```
(array([-3.85682488,  0.23630194]), 30.72004195498317)
```

In [81]:

```
# Predicting the Test set results
y_pred = pr.predict(X_test_p[:,1:])

# Coefficient of determination R^2
pr.score(X_train_p[:,1:], y_train), pr.score(X_test_p[:,1:], y_test)
```

Out[81]:

```
(0.17625737552997145, 0.024673215332501774)
```

Исходя из R^2 делаем вывод, что модель неадеватна и ее нельзя использовать для прогнозирования.

In [82]:

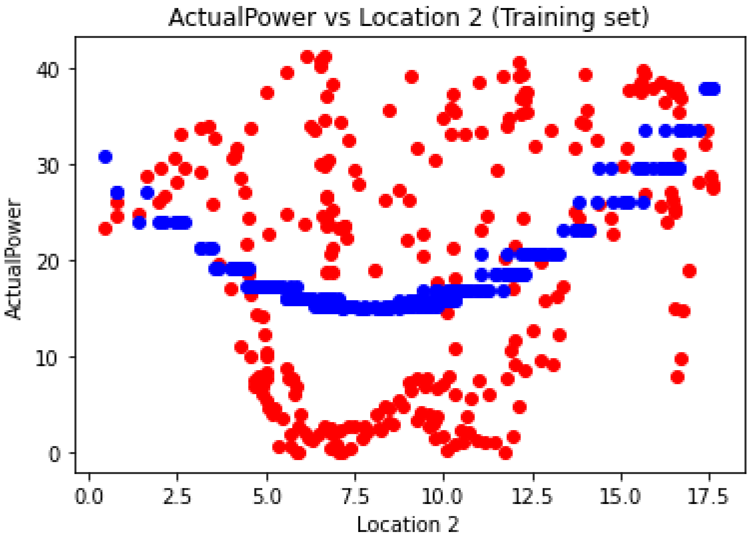
```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, pr.predict(X_train_p[:,1:])), mean_squared_error(y_tes
t, y_pred)
```

Out[82]:

```
(144.11540932058205, 158.61297864667245)
```

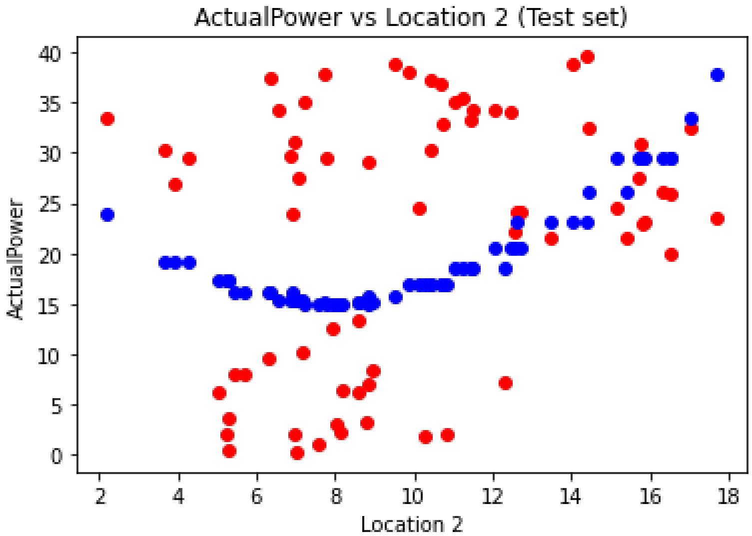
In [83]:

```
# Visualising the Training set results
plt.scatter(X_train[:,3], y_train, color = 'red')
plt.plot(X_train[:,3], pr.predict(X_train_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 2 (Training set)')
plt.xlabel('Location 2')
plt.ylabel('ActualPower')
plt.show()
```



In [84]:

```
# Visualising the Test set results
plt.scatter(X_test[:,3], y_test, color = 'red')
plt.plot(X_test[:,3], pr.predict(X_test_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 2 (Test set)')
plt.xlabel('Location 2')
plt.ylabel('ActualPower')
plt.show()
```



In [85]:

```
# LOCATION 4
# Fitting Polynomial Regression to the dataset
from sklearn.preprocessing import PolynomialFeatures
X_train_p = PolynomialFeatures().fit_transform(X_train[:, 3:4])
X_test_p = PolynomialFeatures().fit_transform(X_test[:, 3:4])
pr = LinearRegression().fit(X_train_p[:,1:], y_train)
```

In [86]:

```
# Getting parameters
pr.coef_, pr.intercept_
```

Out[86]:

```
(array([-3.84259169,  0.23530189]), 30.957378435748 38)
```

In [87]:

```
# Predicting the Test set results
y_pred = pr.predict(X_test_p[:,1:])

# Coefficient of determination R^2
pr.score(X_train_p[:,1:], y_train), pr.score(X_test_p[:,1:], y_test)
```

Out[87]:

```
(0.16480169578227877, -0.003747635541274441)
```

Исходя из R^2 делаем вывод, что модель неадеватна и ее нельзя использовать для прогнозирования.

In [88]:

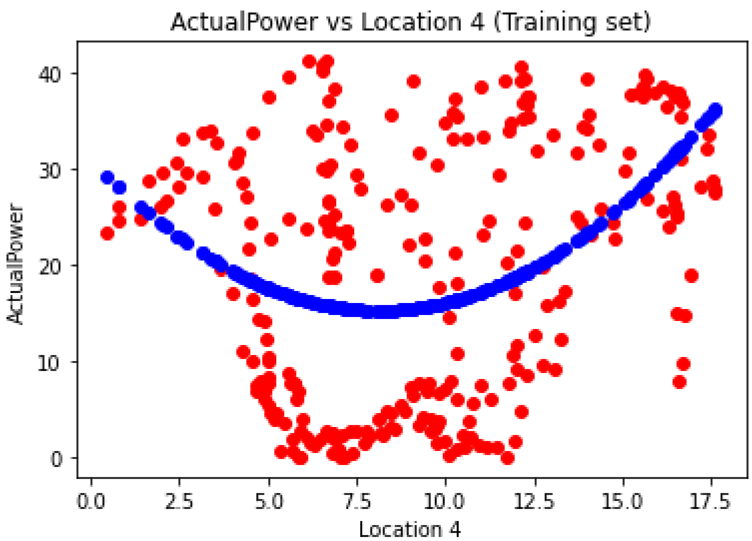
```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, pr.predict(X_train_p[:,1:])), mean_squared_error(y_tes
t, y_pred)
```

Out[88]:

```
(146.11960326034134, 163.2349329327934)
```

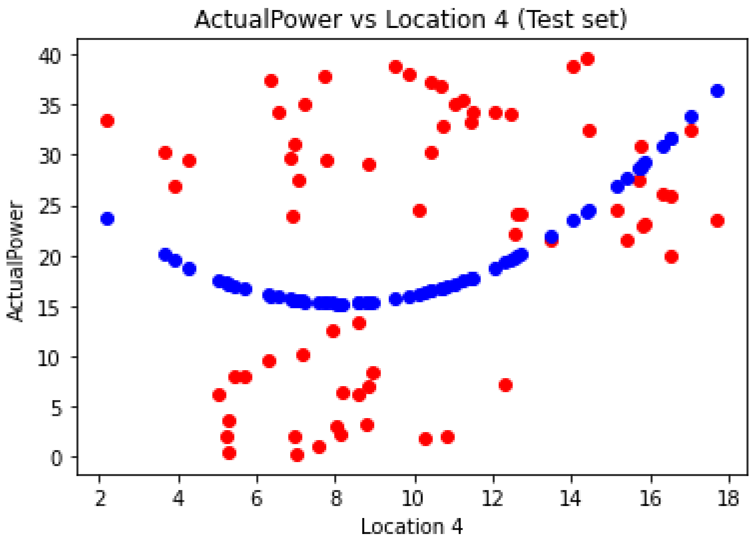
In [89]:

```
# Visualising the Training set results
plt.scatter(X_train[:,3], y_train, color = 'red')
plt.plot(X_train[:,3], pr.predict(X_train_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 4 (Training set)')
plt.xlabel('Location 4')
plt.ylabel('ActualPower')
plt.show()
```



In [90]:

```
# Visualising the Test set results
plt.scatter(X_test[:,3], y_test, color = 'red')
plt.plot(X_test[:,3], pr.predict(X_test_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 4 (Test set)')
plt.xlabel('Location 4')
plt.ylabel('ActualPower')
plt.show()
```



In [91]:

```
# LOCATION 5
# Fitting Polynomial Regression to the dataset
from sklearn.preprocessing import PolynomialFeatures
X_train_p = PolynomialFeatures().fit_transform(X_train[:, 4:5])
X_test_p = PolynomialFeatures().fit_transform(X_test[:, 4:5])
pr = LinearRegression().fit(X_train_p[:,1:], y_train)
```

In [92]:

```
# Getting parameters
pr.coef_, pr.intercept_
```

Out[92]:

```
(array([-6.49270161,  0.5152008 ]), 35.85567252373448)
```

In [93]:

```
# Predicting the Test set results
y_pred = pr.predict(X_test_p[:,1:])

# Coefficient of determination R^2
pr.score(X_train_p[:,1:], y_train), pr.score(X_test_p[:,1:], y_test)
```

Out[93]:

```
(0.1544670383225134, -0.03977764398497907)
```

Исходя из R^2 делаем вывод, что модель неадеватна и ее нельзя использовать для прогнозирования.

In [94]:

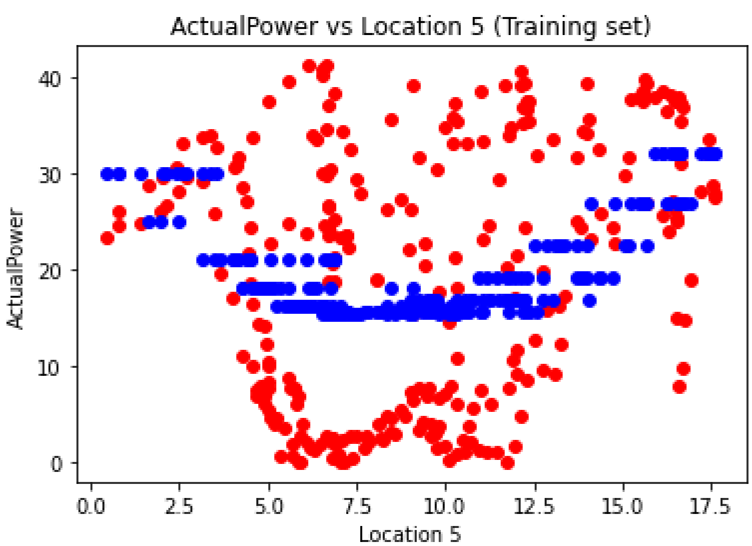
```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, pr.predict(X_train_p[:,1:])), mean_squared_error(y_tes
t, y_pred)
```

Out[94]:

```
(147.92767212282166, 169.0943300597461)
```

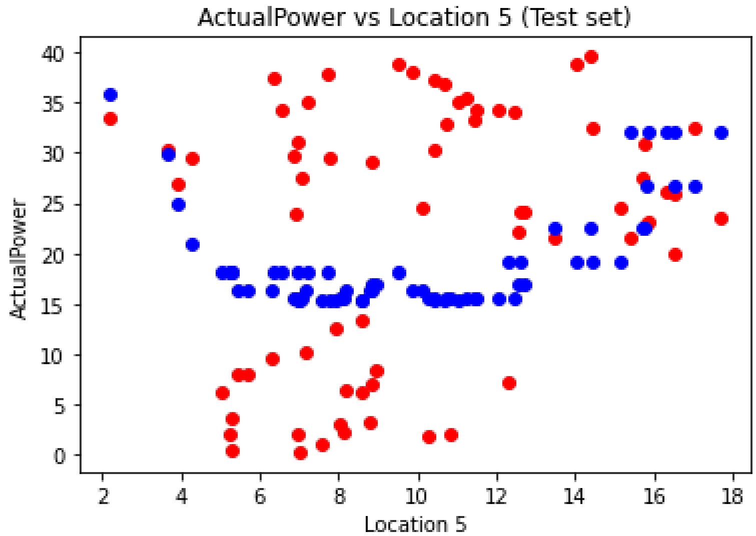
In [95]:

```
# Visualising the Training set results
plt.scatter(X_train[:,3], y_train, color = 'red')
plt.plot(X_train[:,3], pr.predict(X_train_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 5 (Training set)')
plt.xlabel('Location 5')
plt.ylabel('ActualPower')
plt.show()
```



In [96]:

```
# Visualising the Test set results
plt.scatter(X_test[:,3], y_test, color = 'red')
plt.plot(X_test[:,3], pr.predict(X_test_p[:,1:]), 'bo')
plt.title('ActualPower vs Location 5 (Test set)')
plt.xlabel('Location 5')
plt.ylabel('ActualPower')
plt.show()
```



Backward Elimination with p-values

In [109]:

```
# Backward Elimination with p-values
import statsmodels.api as sm
def backwardElimination(x, sl):
    numVars = len(x[0])
    for i in range(0, numVars):
        regressor_OLS = sm.OLS(y, x).fit()
        maxVar = max(regressor_OLS.pvalues).astype(float)
        if maxVar > sl:
            for j in range(0, numVars - i):
                if (regressor_OLS.pvalues[j].astype(float) == maxVar):
                    x = np.delete(x, j, 1)
    regressor_OLS.summary()
    return x

SL = 0.05
X_opt = X_train[:, [0, 1, 2, 3, 4]]
y = y_train
X_Modeled = backwardElimination(X_opt, SL)
```

In [110]:

```
X_Modeled
```

Out[110]:

```
array([[45.   ,  7.   ,  7.503,  6.   ],
       [45.   ,  5.   ,  9.834,  6.   ],
       [45.   ,  6.   ,  6.843,  6.   ],
       ...,
       [45.   ,  3.   ,  5.852,  5.   ],
       [45.   ,  6.   ,  6.647,  5.   ],
       [43.5  ,  8.   , 15.66 , 10.   ]])
```

In [111]:

```
# Fitting Optimized Multiple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
omr = LinearRegression().fit(X_train[:, 0:4], y_train)
```

In [112]:

```
# Getting parameters
omr.coef_, omr.intercept_
```

Out[112]:

```
(array([ 1.28408405,  0.93917498,  2.0397665 , -1.69107672]),
 -48.63860838043068)
```

In [113]:

```
# Predicting the Test set results
y_pred = omr.predict(X_test[:, 0:4])
```

In [114]:

```
# Coefficient of determination R^2
omr.score(X_train[:, 0:4], y_train), omr.score(X_test[:, 0:4], y_test)
```

Out[114]:

```
(0.08747648526264218, 0.18300492954558778)
```

Исходя из R^2 делаем вывод, что модель неадеватна и ее нельзя использовать для прогнозирования.

In [115]:

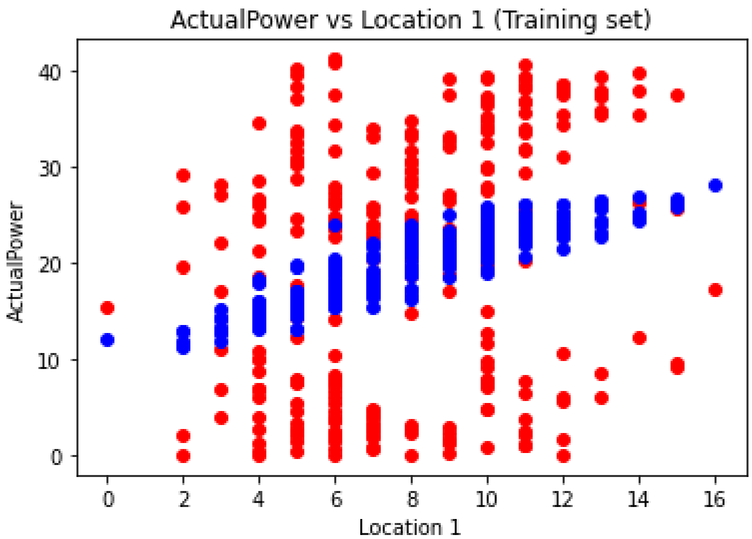
```
# Mean squared error
from sklearn.metrics import mean_squared_error
mean_squared_error(y_train, omr.predict(X_train[:, 0:4])), mean_squared_error(y_te
st, y_pred)
```

Out[115]:

```
(159.64780252283202, 132.86420890060958)
```

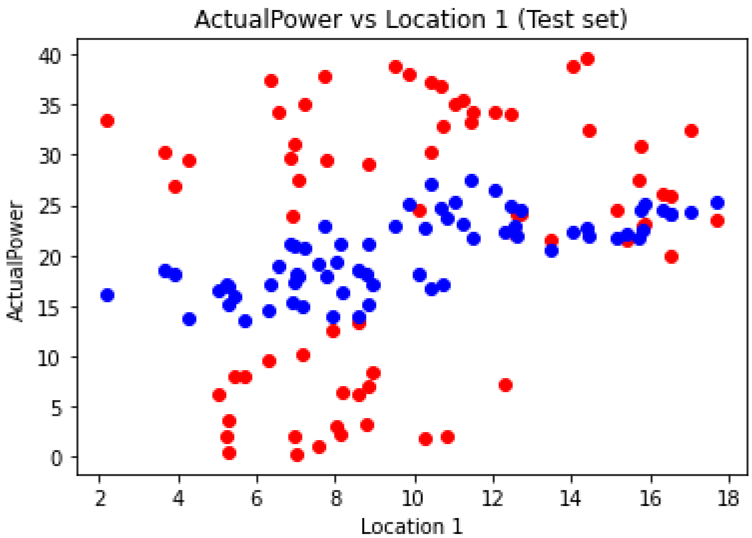
In [116]:

```
# Visualising the Training set results
plt.scatter(X_train[:,1], y_train, color = 'red')
plt.plot(X_train[:,1], omr.predict(X_train[:, 0:4]), 'bo')
plt.title('ActualPower vs Location 1 (Training set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



In [117]:

```
# Visualising the Test set results
plt.scatter(X_test[:,3], y_test, color = 'red')
plt.plot(X_test[:,3], omr.predict(X_test[:, 0:4]), 'bo')
plt.title('ActualPower vs Location 1 (Test set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



Regression Tree & Random Forest

In [131]:

```
# Fitting Tree to the Training set (Location 1)
sdt = DecisionTreeRegressor(max_leaf_nodes = 10).fit(X_train[:, 1:2], y_train)
```

In [132]:

```
# Predicting the Test set results
y_pred = sdt.predict(X_test[:, 1:2])
```

In [133]:

```
# Coefficient of determination R^2
r2 = (sdt.score(X_train[:, 1:2], y_train), sdt.score(X_test[:, 1:2], y_test))
print(f"For Location 1 r2 = {r2}")
```

```
For Location 1 r2 = (0.11815206897979558, 0.08292424988205249)
```

In [134]:

```
# Fitting Tree to the Training set (MaxCapacity)
sdt = DecisionTreeRegressor(max_leaf_nodes = 10).fit(X_train[:, 0:1], y_train)

# Predicting the Test set results
y_pred = sdt.predict(X_test[:, 0:1])

# Coefficient of determination R^2
r2 = (sdt.score(X_train[:, 0:1], y_train), sdt.score(X_test[:, 0:1], y_test))
print(f"For MaxCapacity r2 = {r2}")
```

```
For MaxCapacity r2 = (0.012361222860595933, -0.0338804583810739)
```

In [135]:

```
# Fitting Tree to the Training set (Location 4)
sdt = DecisionTreeRegressor(max_leaf_nodes = 10).fit(X_train[:, 2:3], y_train)

# Predicting the Test set results
y_pred = sdt.predict(X_test[:,2:3])

# Coefficient of determination R^2
r2 = (sdt.score(X_train[:, 2:3], y_train), sdt.score(X_test[:, 2:3], y_test))
print(f"For Location 4 r2 = {r2}")
```

```
For Location 4 r2 = (0.2798805146307243, 0.15844420625327327)
```

In [136]:

```
# Fitting Tree to the Training set (Location 5)
sdt = DecisionTreeRegressor(max_leaf_nodes = 10).fit(X_train[:, 3:4], y_train)

# Predicting the Test set results
y_pred = sdt.predict(X_test[:, 3:4])

# Coefficient of determination R^2
r2 = (sdt.score(X_train[:, 3:4], y_train), sdt.score(X_test[:, 3:4], y_test))
print(f"For Location 5 r2 = {r2}")
```

```
For Location 5 r2 = (0.39045230908331885, -0.05254532334840545)
```

Исходя из R^2 ни одна из моделей не подходит для прогнозирования.

In [137]:

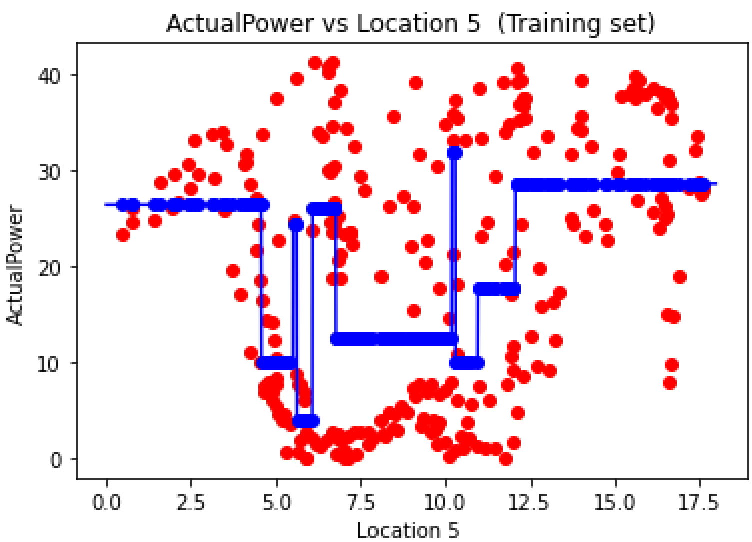
```
# Mean squared error
mean_squared_error(y_train, sdt.predict(X_train[:, 3:4])), mean_squared_error(y_te
st, y_pred)
```

Out[137]:

```
(106.64157998791202, 171.1706799417286)
```

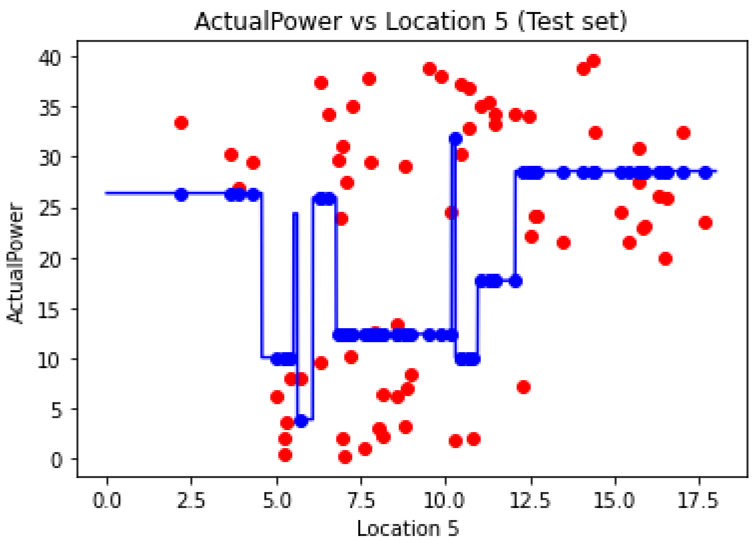
In [138]:

```
# Visualising the Training set results
X_grid = np.arange(min(X[:, 3:4]), max(X[:, 3:4]), 0.01)
X_grid = X_grid.reshape((len(X_grid), 1))
plt.plot(X_grid, sdt.predict(X_grid), color = 'blue')
plt.scatter(X_train[:,3], y_train, color = 'red')
plt.plot(X_train[:,3], sdt.predict(X_train[:, 3:4]), 'bo')
plt.title('ActualPower vs Location 5  (Training set)')
plt.xlabel('Location 5 ')
plt.ylabel('ActualPower')
plt.show()
```



In [139]:

```
# Visualising the Test set results
X_grid = np.arange(min(X[:, 3:4]), max(X[:, 3:4]), 0.01)
X_grid = X_grid.reshape((len(X_grid), 1))
plt.plot(X_grid, sdt.predict(X_grid), color = 'blue')
plt.scatter(X_test[:,3], y_test, color = 'red')
plt.plot(X_test[:,3], sdt.predict(X_test[:, 3:4]), 'bo')
plt.title('ActualPower vs Location 5 (Test set)')
plt.xlabel('Location 5 ')
plt.ylabel('ActualPower')
plt.show()
```



Random Forest

In [153]:

```
# Fitting Random Forest to the Training set
rf = RandomForestRegressor(n_estimators = 10, random_state = 0).fit(X_train, y_tra
in)
```

In [154]:

```
# Predicting the Test set results
y_pred = rf.predict(X_test)

# Coefficient of determination R^2
rf.score(X_train, y_train), rf.score(X_test, y_test)
```

Out[154]:

```
(0.8609475559528259, 0.5885741186947391)
```

R^2 для тренировочной выборки показал отличный результат, для тестовой - значение немного меньше за 0,6. Это говорит о том, что на данный момент именно модель Random Forest лучше всего подходит для целей прогнозирования этой выборки данных.

In [155]:

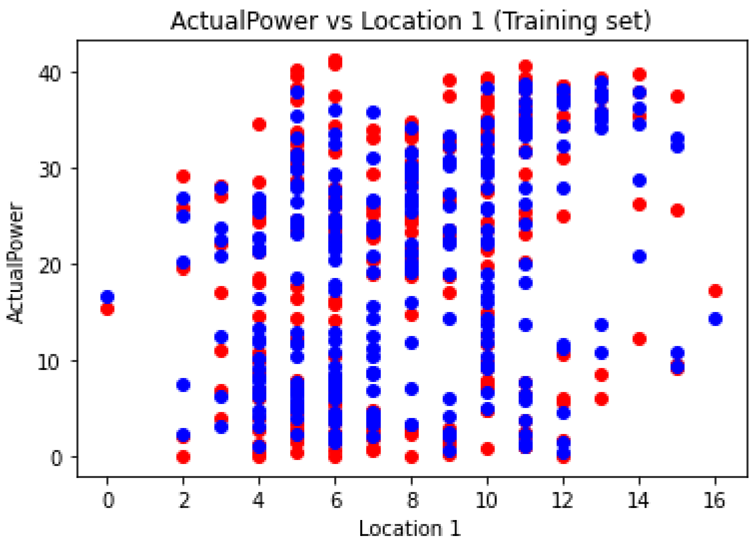
```
# Mean squared error
mean_squared_error(y_train, rf.predict(X_train)), mean_squared_error(y_test, y_pre
d)
```

Out[155]:

```
(24.327501449592596, 66.90832811323529)
```

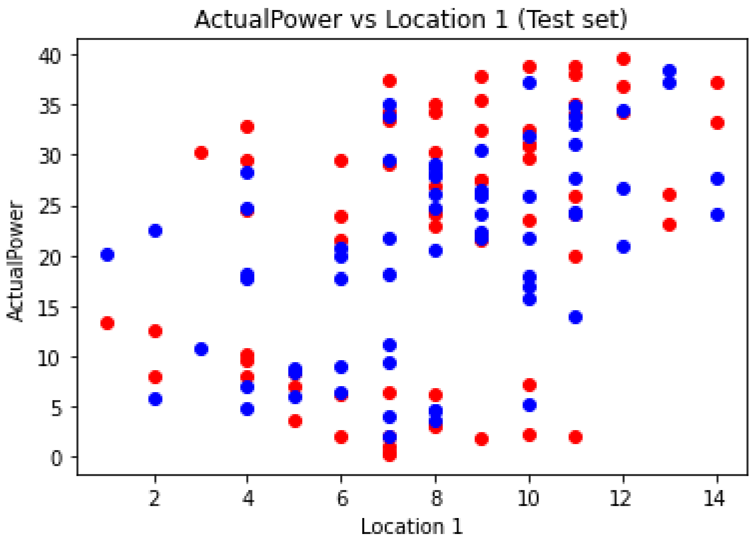
In [156]:

```
# Visualising the Training set results
plt.scatter(X_train[:,1], y_train, color = 'red')
plt.plot(X_train[:,1], rf.predict(X_train), 'bo')
plt.title('ActualPower vs Location 1 (Training set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



In [157]:

```
# Visualising the Test set results
plt.scatter(X_test[:,1], y_test, color = 'red')
plt.plot(X_test[:,1], rf.predict(X_test), 'bo')
plt.title('ActualPower vs Location 1 (Test set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



Regression Neural Network

In [159]:

```
# Feature Scaling
sc = StandardScaler()
dfsc = sc.fit_transform(df)
df['ActualPower'] = dfsc[:,0]
df['Max Capacity'] = dfsc[:,1]
df['Location 1'] = dfsc[:,2]
df['Location 2'] = dfsc[:,3]
df['Location 4'] = dfsc[:,4]
df['Location 5'] = dfsc[:,5]
```

In [160]:

```
df
```

Out[160]:

	ActualPower	Max Capacity	Location 1	Location 2	Location 4	Location 5
0	-1.239557	0.469272	-0.622071	-0.125768	0.101909	0.124568
1	-1.262345	0.469272	-0.950089	-0.125768	0.079358	0.481382
2	-1.219048	0.469272	-1.278108	-0.125768	0.049209	0.481382
3	-1.004918	0.469272	-1.278108	-0.125768	0.008274	0.481382
4	-0.934731	0.469272	-0.950089	-0.125768	-0.041240	0.481382
...	...	...	...	...	...	...
333	0.396157	0.469272	-0.294052	-0.603405	-0.625115	-1.302688
334	0.096724	0.469272	0.033966	-0.603405	-0.615800	-1.302688
335	-0.102670	0.469272	0.033966	-0.603405	-0.618006	-1.302688
336	0.049478	0.469272	0.033966	-0.842224	-0.630262	-1.302688
337	-0.091959	0.469272	0.361985	-0.842224	-0.666295	-1.302688

338 rows × 6 columns

In [162]:

```
# Cheking correlations
correlation = df.corr()
correlation.style.background_gradient(cmap='coolwarm')
```

Out[162]:

	ActualPower	Max Capacity	Location 1	Location 2	Location 4	Location 5
ActualPower	1.000000	-0.099136	0.297014	0.268269	0.256173	0.113401
Max Capacity	-0.099136	1.000000	-0.429784	-0.429683	-0.422071	-0.398832
Location 1	0.297014	-0.429784	1.000000	0.639311	0.648041	0.580977
Location 2	0.268269	-0.429683	0.639311	1.000000	0.992052	0.911672
Location 4	0.256173	-0.422071	0.648041	0.992052	1.000000	0.937005
Location 5	0.113401	-0.398832	0.580977	0.911672	0.937005	1.000000

In [181]:

```
# Splitting the dataset into the Training set and Test set
X = df.iloc[:, 1:6].values
y = df.iloc[:, 0].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_st
ate=0)
```

In [182]:

```
# Initialising the ANN
rnn = Sequential()

# Adding the input layer and the first hidden layer
rnn.add(Dense(units = 6, activation = 'tanh', input_dim = 5))

# Adding the second hidden layer
rnn.add(Dense(units = 6, activation = 'tanh'))

# Adding the output layer
rnn.add(Dense(units = 1, activation = 'linear'))

# Compiling the ANN
rnn.compile(optimizer='adam', loss='mean_squared_error', metrics = ['accuracy'])
```

In [183]:

```
# Fitting the ANN to the Training set
rnn.fit(X_train, y_train, batch_size = 10, epochs = 100)
```

```
Epoch 1/100
27/27 [==============================] - 0s 937us/step - loss: 0.9373
- accuracy: 0.0000e+00
Epoch 2/100
27/27 [==============================] - 0s 1ms/step - loss: 0.9199 -
accuracy: 0.0000e+00
Epoch 3/100
27/27 [==============================] - 0s 1ms/step - loss: 0.9092 -
accuracy: 0.0000e+00
Epoch 4/100
27/27 [==============================] - 0s 1ms/step - loss: 0.9023 -
accuracy: 0.0000e+00
Epoch 5/100
27/27 [==============================] - 0s 1ms/step - loss: 0.8963 -
accuracy: 0.0000e+00
Epoch 6/100
27/27 [==============================] - 0s 1ms/step - loss: 0.8915 -
accuracy: 0.0000e+00
Epoch 7/100
27/27 [==============================] - 0s 951us/step - loss: 0.8908
- accuracy: 0.0000e+00
Epoch 8/100
27/27 [==============================] - 0s 812us/step - loss: 0.8821
- accuracy: 0.0000e+00
Epoch 9/100
27/27 [==============================] - 0s 2ms/step - loss: 0.8776 -
accuracy: 0.0000e+00
Epoch 10/100
27/27 [==============================] - 0s 1ms/step - loss: 0.8744 -
accuracy: 0.0000e+00
Epoch 11/100
27/27 [==============================] - 0s 782us/step - loss: 0.8691
- accuracy: 0.0000e+00
Epoch 12/100
27/27 [==============================] - 0s 2ms/step - loss: 0.8640 -
accuracy: 0.0000e+00
Epoch 13/100
27/27 [==============================] - 0s 895us/step - loss: 0.8605
- accuracy: 0.0000e+00
Epoch 14/100
27/27 [==============================] - 0s 835us/step - loss: 0.8539
- accuracy: 0.0000e+00
Epoch 15/100
27/27 [==============================] - 0s 1ms/step - loss: 0.8492 -
accuracy: 0.0000e+00
Epoch 16/100
27/27 [==============================] - 0s 945us/step - loss: 0.8442
- accuracy: 0.0000e+00
Epoch 17/100
27/27 [==============================] - 0s 942us/step - loss: 0.8383
- accuracy: 0.0000e+00
Epoch 18/100
27/27 [==============================] - 0s 733us/step - loss: 0.8328
- accuracy: 0.0000e+00
Epoch 19/100
27/27 [==============================] - 0s 2ms/step - loss: 0.8279 -
accuracy: 0.0000e+00
```

```
Epoch 20/100
27/27 [==============================] - 0s 1ms/step - loss: 0.8219 -
accuracy: 0.0000e+00
Epoch 21/100
27/27 [==============================] - 0s 1ms/step - loss: 0.8155 -
accuracy: 0.0000e+00
Epoch 22/100
27/27 [==============================] - 0s 755us/step - loss: 0.8088
- accuracy: 0.0000e+00
Epoch 23/100
27/27 [==============================] - 0s 1ms/step - loss: 0.8015 -
accuracy: 0.0000e+00
Epoch 24/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7960 -
accuracy: 0.0000e+00
Epoch 25/100
27/27 [==============================] - 0s 917us/step - loss: 0.7883
- accuracy: 0.0000e+00
Epoch 26/100
27/27 [==============================] - 0s 841us/step - loss: 0.7817
- accuracy: 0.0000e+00
Epoch 27/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7750 -
accuracy: 0.0000e+00
Epoch 28/100
27/27 [==============================] - 0s 892us/step - loss: 0.7685
- accuracy: 0.0000e+00
Epoch 29/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7604 -
accuracy: 0.0000e+00
Epoch 30/100
27/27 [==============================] - 0s 835us/step - loss: 0.7541
- accuracy: 0.0000e+00
Epoch 31/100
27/27 [==============================] - 0s 2ms/step - loss: 0.7472 -
accuracy: 0.0000e+00
Epoch 32/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7411 -
accuracy: 0.0000e+00
Epoch 33/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7362 -
accuracy: 0.0000e+00
Epoch 34/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7283 -
accuracy: 0.0000e+00
Epoch 35/100
27/27 [==============================] - 0s 813us/step - loss: 0.7242
- accuracy: 0.0000e+00
Epoch 36/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7145 -
accuracy: 0.0000e+00
Epoch 37/100
27/27 [==============================] - 0s 926us/step - loss: 0.7091
- accuracy: 0.0000e+00
Epoch 38/100
27/27 [==============================] - 0s 1ms/step - loss: 0.7063 -
accuracy: 0.0000e+00
```

```
Epoch 39/100
27/27 [==============================] - 0s 973us/step - loss: 0.6988
- accuracy: 0.0000e+00
Epoch 40/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6946 -
accuracy: 0.0000e+00
Epoch 41/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6872 -
accuracy: 0.0000e+00
Epoch 42/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6844 -
accuracy: 0.0000e+00
Epoch 43/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6794 -
accuracy: 0.0000e+00
Epoch 44/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6763 -
accuracy: 0.0000e+00
Epoch 45/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6739 -
accuracy: 0.0000e+00
Epoch 46/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6691 -
accuracy: 0.0000e+00
Epoch 47/100
27/27 [==============================] - 0s 2ms/step - loss: 0.6650 -
accuracy: 0.0000e+00
Epoch 48/100
27/27 [==============================] - 0s 2ms/step - loss: 0.6640 -
accuracy: 0.0000e+00
Epoch 49/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6582 -
accuracy: 0.0000e+00
Epoch 50/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6575 -
accuracy: 0.0000e+00
Epoch 51/100
27/27 [==============================] - 0s 782us/step - loss: 0.6537
- accuracy: 0.0000e+00
Epoch 52/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6518 -
accuracy: 0.0000e+00
Epoch 53/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6483 -
accuracy: 0.0000e+00
Epoch 54/100
27/27 [==============================] - 0s 2ms/step - loss: 0.6474 -
accuracy: 0.0000e+00
Epoch 55/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6442 -
accuracy: 0.0000e+00
Epoch 56/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6435 -
accuracy: 0.0000e+00
Epoch 57/100
27/27 [==============================] - 0s 869us/step - loss: 0.6418
- accuracy: 0.0000e+00
```

```
Epoch 58/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6409 -
accuracy: 0.0000e+00
Epoch 59/100
27/27 [==============================] - 0s 956us/step - loss: 0.6391
- accuracy: 0.0000e+00
Epoch 60/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6339 -
accuracy: 0.0000e+00
Epoch 61/100
27/27 [==============================] - 0s 987us/step - loss: 0.6313
- accuracy: 0.0000e+00
Epoch 62/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6285 -
accuracy: 0.0000e+00
Epoch 63/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6347 -
accuracy: 0.0000e+00
Epoch 64/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6264 -
accuracy: 0.0000e+00
Epoch 65/100
27/27 [==============================] - 0s 895us/step - loss: 0.6248
- accuracy: 0.0000e+00
Epoch 66/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6240 -
accuracy: 0.0000e+00
Epoch 67/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6226 -
accuracy: 0.0000e+00
Epoch 68/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6225 -
accuracy: 0.0000e+00
Epoch 69/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6204 -
accuracy: 0.0000e+00
Epoch 70/100
27/27 [==============================] - 0s 888us/step - loss: 0.6178
- accuracy: 0.0000e+00
Epoch 71/100
27/27 [==============================] - 0s 799us/step - loss: 0.6188
- accuracy: 0.0000e+00
Epoch 72/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6178 -
accuracy: 0.0000e+00
Epoch 73/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6178 -
accuracy: 0.0000e+00
Epoch 74/100
27/27 [==============================] - 0s 930us/step - loss: 0.6150
- accuracy: 0.0000e+00
Epoch 75/100
27/27 [==============================] - 0s 915us/step - loss: 0.6147
- accuracy: 0.0000e+00
Epoch 76/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6136 -
accuracy: 0.0000e+00
```

```
Epoch 77/100
27/27 [==============================] - 0s 915us/step - loss: 0.6157
- accuracy: 0.0000e+00
Epoch 78/100
27/27 [==============================] - 0s 856us/step - loss: 0.6108
- accuracy: 0.0000e+00
Epoch 79/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6112 -
accuracy: 0.0000e+00
Epoch 80/100
27/27 [==============================] - 0s 929us/step - loss: 0.6101
- accuracy: 0.0000e+00
Epoch 81/100
27/27 [==============================] - 0s 850us/step - loss: 0.6093
- accuracy: 0.0000e+00
Epoch 82/100
27/27 [==============================] - 0s 813us/step - loss: 0.6077
- accuracy: 0.0000e+00
Epoch 83/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6068 -
accuracy: 0.0000e+00
Epoch 84/100
27/27 [==============================] - 0s 994us/step - loss: 0.6112
- accuracy: 0.0000e+00
Epoch 85/100
27/27 [==============================] - 0s 796us/step - loss: 0.6108
- accuracy: 0.0000e+00
Epoch 86/100
27/27 [==============================] - 0s 968us/step - loss: 0.6064
- accuracy: 0.0000e+00
Epoch 87/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6063 -
accuracy: 0.0000e+00
Epoch 88/100
27/27 [==============================] - 0s 824us/step - loss: 0.6042
- accuracy: 0.0000e+00
Epoch 89/100
27/27 [==============================] - 0s 886us/step - loss: 0.6042
- accuracy: 0.0000e+00
Epoch 90/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6044 -
accuracy: 0.0000e+00
Epoch 91/100
27/27 [==============================] - 0s 840us/step - loss: 0.6043
- accuracy: 0.0000e+00
Epoch 92/100
27/27 [==============================] - 0s 2ms/step - loss: 0.6036 -
accuracy: 0.0000e+00
Epoch 93/100
27/27 [==============================] - 0s 892us/step - loss: 0.6022
- accuracy: 0.0000e+00
Epoch 94/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6022 -
accuracy: 0.0000e+00
Epoch 95/100
27/27 [==============================] - 0s 1ms/step - loss: 0.6032 -
accuracy: 0.0000e+00
```

```
Epoch 96/100
27/27 [==============================] - 0s 965us/step - loss: 0.5997
- accuracy: 0.0000e+00
Epoch 97/100
27/27 [==============================] - 0s 756us/step - loss: 0.6005
- accuracy: 0.0000e+00
Epoch 98/100
27/27 [==============================] - 0s 769us/step - loss: 0.5998
- accuracy: 0.0000e+00
Epoch 99/100
27/27 [==============================] - 0s 1ms/step - loss: 0.5998 -
accuracy: 0.0000e+00
Epoch 100/100
27/27 [==============================] - 0s 907us/step - loss: 0.5997
- accuracy: 0.0000e+00
```

Out[183]:

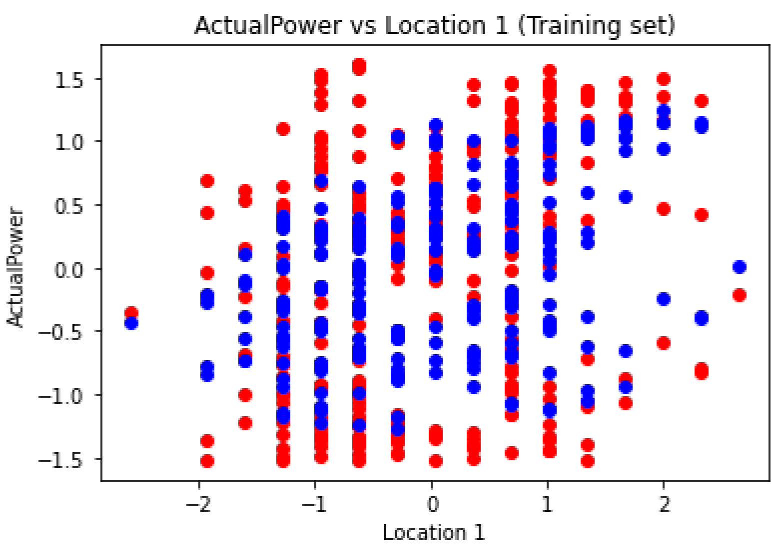
```
<tensorflow.python.keras.callbacks.History at 0x7fb6ac782490>
```

In [184]:

```
# Predicting the Test set results
y_pred = rnn.predict(X_test)
```

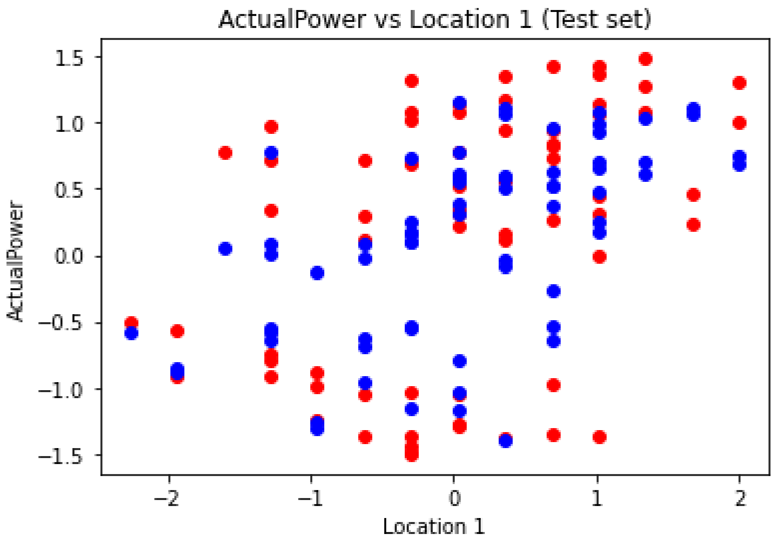
In [185]:

```
# Visualising the Training set results
plt.scatter(X_train[:,1], y_train, color = 'red')
plt.plot(X_train[:,1], rnn.predict(X_train), 'bo')
plt.title('ActualPower vs Location 1 (Training set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



In [186]:

```
# Visualising the Test set results
plt.scatter(X_test[:,1], y_test, color = 'red')
plt.plot(X_test[:,1], rnn.predict(X_test), 'bo')
plt.title('ActualPower vs Location 1 (Test set)')
plt.xlabel('Location 1')
plt.ylabel('ActualPower')
plt.show()
```



p_nn <- predict(nn, f_test) train_mse_nn <- sum((f_train$price-predict(nn, f_train))^2)/length(f_train$price) test_mse_nn <- sum((f_test$price-p_nn)^2)/length(p_nn) train_mse_nn

[1] 0.104495

test_mse_nn

[1] 0.2036023

In [191]:

```
train_mse_nn = sum((y_train-rnn.predict(X_train))**2)/len(y_train)
train_mse_nn
```

Out[191]:

```
array([2.03596252, 0.42115171, 2.15799916, 0.40279542, 0.94599067,
       1.07830781, 0.42068653, 1.2598147 , 2.58355487, 1.24985008,
       1.53688343, 2.44665471, 1.16994849, 0.44868573, 0.43750575,
       1.89001147, 2.05134273, 1.54481381, 0.82154317, 0.97748886,
       2.460344  , 0.81155877, 2.11477668, 0.53406456, 2.62869146,
       1.38692683, 1.26163174, 0.45626691, 0.70227614, 0.66900023,
       0.40659658, 0.96135595, 1.76823523, 0.404817  , 1.65490088,
       2.33479407, 0.48115675, 3.11247481, 1.67213887, 0.46140397,
       0.57537574, 1.00941012, 1.15828579, 2.57525929, 1.90711308,
       1.81281864, 1.6733212 , 1.75284382, 0.41931824, 0.53920462,
       1.8477026 , 0.55880674, 1.46395013, 0.49976318, 0.40384463,
       0.92029086, 2.99569349, 2.44142249, 3.00181447, 2.21053595,
       0.51938695, 1.11682639, 2.33692769, 2.19119565, 0.81019774,
       0.65176117, 0.92445777, 0.60499252, 1.3550644 , 0.54289506,
       2.20994294, 0.63458214, 2.41010176, 2.47390296, 2.72192526,
       1.01510958, 1.23077349, 1.82912689, 1.43732507, 0.57996836,
       2.41740806, 2.17596504, 1.65386394, 0.53395391, 2.27216947,
       2.20747216, 0.48136725, 1.61692265, 1.04595568, 1.51095378,
       1.00537757, 0.4050242 , 1.78820028, 0.53718166, 0.55934971,
       2.004841  , 2.61307475, 0.49981549, 0.50689763, 2.08192529,
       1.29048727, 2.57391555, 0.46173943, 1.28775366, 0.66923606,
       1.19790064, 2.02587815, 2.00080372, 1.94370241, 1.60056366,
       0.48331672, 2.07562905, 0.463238  , 0.62399394, 0.97980866,
       1.1374165 , 0.40137514, 2.03227423, 2.48154338, 2.12994271,
       1.32810776, 1.20170155, 1.86307244, 1.68345008, 0.70418772,
       0.4018638 , 2.26137996, 2.69492763, 0.65435247, 1.4842476 ,
       0.84085461, 2.39911475, 2.56787387, 2.36192731, 2.30074509,
       2.19605695, 0.42219267, 1.5209133 , 1.78623302, 2.02568452,
       2.12672892, 1.51657744, 0.96146964, 1.78016121, 0.5490179 ,
       1.1026464 , 2.61194524, 0.87451922, 2.11040461, 0.49739956,
       1.61792782, 1.43593391, 0.40289448, 0.9894384 , 0.43085783,
       0.51073181, 2.57167691, 0.41195839, 0.76719527, 1.85520313,
       1.46818255, 0.432979  , 1.31848051, 2.35005397, 1.78301687,
       2.65461336, 2.46691024, 2.27903285, 1.2076927 , 0.44003482,
       2.06387458, 0.5168385 , 0.42707235, 0.70302662, 0.53439139,
       1.212748  , 1.09882259, 0.6671097 , 1.6570964 , 0.47919505,
       2.25080807, 0.89918062, 0.6837372 , 0.73944185, 1.88188502,
       1.22511063, 1.83492387, 2.26986419, 0.83955614, 1.99734725,
       2.54001271, 0.62679821, 2.12714754, 2.88291873, 1.4305327 ,
       0.75543804, 1.07456321, 1.36429945, 2.6541573 , 1.32810776,
       2.25308138, 0.40978682, 1.52477446, 1.008688  , 0.84772973,
       2.49163464, 1.43423486, 0.92975585, 2.08409235, 0.75065443,
       1.16343627, 2.15115992, 1.88188502, 1.31051036, 2.03072251,
       1.56998398, 2.28630554, 0.7331119 , 2.16162534, 1.26828085,
       1.08181214, 2.15196384, 1.18184768, 2.33014959, 1.21083333,
       2.78131356, 0.48956324, 0.49981549, 1.75390368, 0.69202335,
       0.5700872 , 0.55413433, 0.86484066, 2.38413318, 0.4878572 ,
       2.37001889, 0.81848642, 1.69640065, 1.64368351, 0.88375978,
       1.67693855, 1.9465153 , 0.6564965 , 2.20892155, 1.0661018 ,
       0.5235407 , 2.28153174, 1.54595124, 0.40529618, 0.59357197,
       1.24231031, 1.40710256, 1.12754429, 2.37046605, 0.54785272,
       1.22869946, 2.11360316, 0.54895953, 2.35151803, 2.48989933,
       0.46396174, 1.1896514 , 1.68827107, 1.87173574, 1.36012983,
       1.56702974, 2.27799214, 1.32927811, 3.10023174, 0.72063146])
```

In [198]:

```
y_pred_train = rnn.predict(X_train)
y_pred_test = rnn.predict(X_test)
train_mse_nn = sum((y_train - y_pred_train) ** 2 for y_train, y_pred_train in zip(
y_train, y_pred_train)) / len(y_train)
test_mse_nn = sum((y_test - y_pred_test) ** 2 for y_test, y_pred_test in zip(y_tes
t, y_pred_test)) / len(y_test)
print(f"train_mse_nn: {train_mse_nn}, test_mse_nn: {test_mse_nn}")
```

```
train_mse_nn: [0.5959342], test_mse_nn: [0.53254324]
```

ВЫВОД: для прогнозирования данного датасета лучше всего себя показали Random Forest (r^2_test = 0.86, r^2_train = 0.589) и Regression Neural Network. Но учитывая SME, который для Random Forest равен (train = 106.64, test = 171.17) и для RNN - (train=0.6, test=0.53) соответственно, можно сказать, что нейронная модель подходит лучше.