Location estimation using RSSI of wireless LAN

Team C-LAMP

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Introduction

In this project, our aim is to build a model to predict location of nodes based on RSSI readings from Access Points. The data for the project was provided by RISING, Japan for the problem ITU-ML5G-PS-016: Location estimation using RSSI of wireless LAN - organied as a part of the "ITU AI/ML in 5G Challenge: applying machine learning in communication networks".

This project is divided into the following phases:

- Phase 1: Emphasis is given on data preprocessing and exploration ,which will be covered in this report. Following this the data and its attributes are described. Following this data preprocessing and transformation is done to efficiently fit the developed models.
- Phase 2: Prediction model building is covered in this phase of the project.

Background about RSSI

- RSSI is ten times the logarithm of the ratio of power of the received signal and a reference power.
- Power dissipates from a point source as it moves further out and the relationship between power and distance is that power is inversely proportional to the square of the distance travelled.
- A direct theoretical relationship exist between RSSI and distance:

$$\overline{RSSI} = \bar{A} - 10n\log(d)$$

- With the distance of an unknown point known from a set of known points, its location can be estimated.
- RSSI based technique is especially popular among researchers as it is readily available and no extra hardware is required.

Established Localization Techniques

Multilateration:

If we can calculate the distance of a point from a set of 3 or more points whose location is known, we can localize the unknown point.

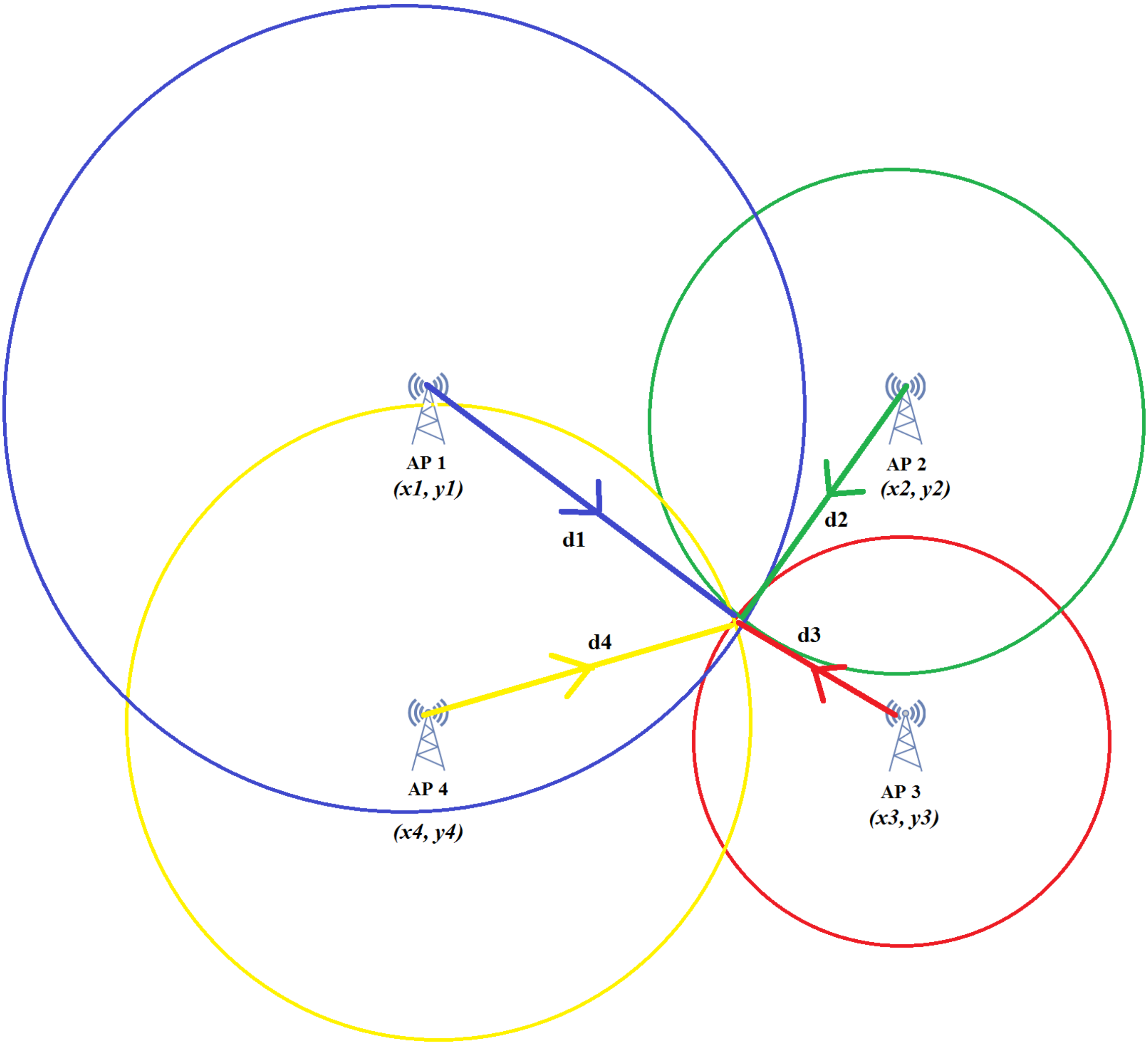
In our scenario we have the following known parameters:

- Location of the four APs (xi ,yi)
- RSSI value measured at AP

The following parameters are unknown and we must figure them out to undertake localization:

- Distance of the RP from each AP (di)
- Location of the RP (x,y)

Distance measurement from RSSI:



As RSSI conveys information about strength of received signal, a relationship exists between RSSI and distance.

$$d = 10^{(\bar{A}-RSSI)/10n}$$

n – Path loss Index (depends on Transmission environment)

A - Average measured RSSI when the AP is 1 meter away from RP

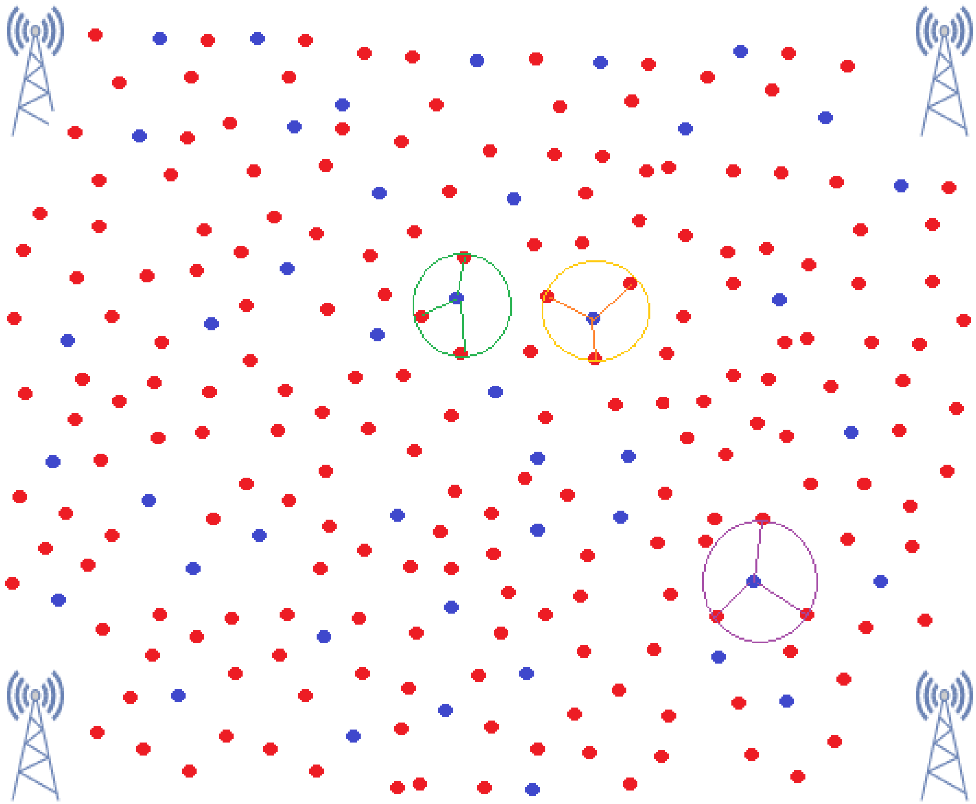
n, A can be found by proper experimentation in the environment.

RSSI Fingerprinting:

In this method we directly estimate the location of the reference point without calculating its distance from the access point.

Precondition for using Fingerprinting:

Presence of large number of Reference Points in the training dataset, uniformly spread throughout the area.



Algorithms used for fingerprinting technique:

k-Nearest Neighbour.

Advantages of using fingerprinting technique:

High Accuracy in localization.

Disadvantages of using fingerprinting technique:

- Thorough Training phase required.
- Sensitive to changes in Environment

Dataset

The provided data sets consist of the following files:

1. AP_info.csv: CSV file providing the location (Latitude, Longitude) and environmental specification for a set of 4 access points (hereby referred to as APs).
2. training_dataset.csv: CSV file providing us with the data acquired from four APs to be used for training the model.

   Data includes :

   - TimeStamp(UNIX)
   - Latitude of Reference Point
   - Longitude of Reference Point
   - SSID of Access Point
   - Channel

- RSSI(dBm)

Data from 13 unique reference points are present in this dataset.

3. verification_dataset.csv: CSV file providing us with the data acquired from the four APs to be used for testing the model.

   Data includes :

   - TimeStamp(UNIX)
   - Latitude of Reference Point
   - Longitude of Reference Point
   - SSID of Access Point
   - Channel
   - RSSI(dBm)

   Data from 13 unique reference points are present in this dataset.

The data in the datasets training_dataset.csv and verification_dataset.csv have been collected from the same set of 4 APs at identical location.

The data set also contains a timestamp on when the RSSI readings of the 4 APs was made. The each data set has 5200 observations.

A map of the reference and the access points was provided with the dataset, as shown below:

Data Pre-processing

Preliminaries

The following Python packages were used in this project.

```
import numpy
import pandas
import tensorflow
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
```

A short mentioning of the used packages:

- **numpy has been used for high-level mathematical functions**
- **pandas has been mainly used for data manipulation and analysis.**
- **tensorflow was used for training and inference of deep neural networks.**
- **sklearn has many inbuilt functions containing various classification and regression algorithms which were used in this project**
- **matplotlib was used in plotting various kinds of graphs and charts**

In [1]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import tensorflow as tf
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
import seaborn as sns
import os
import time
cwd = os.getcwd()
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount(
"/content/drive", force_remount=True).
```

Storing the path names

In [2]:

```
AP_train_path='/content/drive/MyDrive/CDAC/RSSI Dataset Grand Finale/AP_info.csv'
Wifi_train_path ='/content/drive/MyDrive/CDAC/RSSI Dataset Grand Finale/training_dataset.c
sv'
Wifi_test_path ='/content/drive/MyDrive/CDAC/RSSI Dataset Grand Finale/verification_datase
t.csv'
```

Reading the csv files and storing in form of dataset

In [3]:

```
AP_train=pd.read_csv(AP_train_path)
```

Transforming the categorical data to numerical ones using one-hot-encoding

In [4]:

```
AP_train = pd.concat([AP_train,pd.get_dummies(AP_train['Indoor/Outdoor'])['Outdoor']], axi
s=1, join='inner').drop(columns=['Indoor/Outdoor'])
```

Let us have a look at the AP provided information

In [5]:

```
AP_train
```

Out[5]:

	AP SSID	Latitude	Longitude	Hight Difference(m)	Outdoor
0	1	35.157320	136.926447	0	1
1	2	35.157347	136.926807	0	1
2	3	35.157202	136.926827	0	1
3	4	35.157165	136.926470	0	1

In [6]:

```
AP_train = AP_train.astype({"Latitude":'float64',"Longitude":'float64',"Hight Difference(m
)":'float64'})
```

Reading the measured data from the APs from training_dataset.csv and verification_dataset.csv and storing them inform of datasets.

In [7]:

```
train = pd.read_csv(Wifi_train_path)
test = pd.read_csv(Wifi_test_path)
```

In [8]:

```
train.drop(columns=['No.'], inplace=True)
test.drop(columns=['No.'], inplace=True)
```

Having a look at the datasets:

In [9]:

```
train
```

Out[9]:

	TimeStamp(UNIX)	Latitude	Longitude	SSID	Channel	RSSI(dBm)
0	1631687696	35.157140	136.926306	1	11	-41
1	1631687697	35.157140	136.926306	1	11	-41
2	1631687697	35.157140	136.926306	1	11	-41
3	1631687697	35.157140	136.926306	1	11	-41
4	1631687697	35.157140	136.926306	1	11	-41
...	...	...	...	...	...	...
5195	1631688763	35.157236	136.926489	4	1	-52
5196	1631688763	35.157236	136.926489	4	1	-52
5197	1631688763	35.157236	136.926489	4	1	-52
5198	1631688763	35.157236	136.926489	4	1	-52
5199	1631688763	35.157236	136.926489	4	1	-52

5200 rows × 6 columns

In [10]:

```
test
```

Out[10]:

	TimeStamp(UNIX)	Latitude	Longitude	SSID	Channel	RSSI(dBm)
0	1631689137	35.157261	136.926465	1	11	-41
1	1631689137	35.157261	136.926465	1	11	-41
2	1631689138	35.157261	136.926465	1	11	-41
3	1631689138	35.157261	136.926465	1	11	-41
4	1631689138	35.157261	136.926465	1	11	-41
...	...	...	...	...	...	...
5195	1631691291	35.157298	136.926575	4	1	-59
5196	1631691291	35.157298	136.926575	4	1	-59

	TimeStamp(UNIX)	Latitude	Longitude	SSID	Channel	RSSI(dBm)
5197	1631691291	35.157298	136.926575	4	1	-59
5198	1631691291	35.157298	136.926575	4	1	-59
5199	1631691292	35.157298	136.926575	4	1	-59

5200 rows × 6 columns

Removing the duplicate data present :

In [11]:

```
train.drop_duplicates(subset=['TimeStamp(UNIX)','Latitude','Longitude','SSID','RSSI(dBm)'
],keep='first',inplace=True)
test.drop_duplicates(subset=['TimeStamp(UNIX)','Latitude','Longitude','SSID','RSSI(dBm)']
,keep='first',inplace=True)
train.reset_index(inplace=True, drop=True)
test.reset_index(inplace=True, drop=True)
```

Merging the information of APs with the training and testing data:

In [12]:

```
train_semi = train.merge(AP_train, how='inner', left_on='SSID', right_on='AP SSID').drop(
columns=['AP SSID'])
test_semi = test.merge(AP_train, how='inner', left_on='SSID', right_on='AP SSID').drop(col
umns=['AP SSID'])
```

Renaming the columns to make it more comprehensible

In [13]:

```
train_semi.rename(columns = {'Latitude_x':'Latitude_OP','Longitude_x':'Longitude_OP', 'Lat
itude_y':'Latitude_AP', 'Longitude_y':'Longitude_AP'},inplace=True)
test_semi.rename(columns = {'Latitude_x':'Latitude_OP','Longitude_x':'Longitude_OP', 'Lati
tude_y':'Latitude_AP', 'Longitude_y':'Longitude_AP'},inplace=True)
```

As according to the research done in this domain, there is a clear cut relationship between RSSI and euclidean distance between the AP and the reference point (as shown in the formula below), hence we add a feature of the same.

In [14]:

```
def euclidean_dist(lat_op, long_op, lat_ap, long_ap, height):
  return  (((lat_op - lat_ap)*111000)**2 + ((long_op - long_ap)*111000)**2 + height**2)**0
.5
```

Since, we observe a significant variation in the provided RSSI data values (possibly due to multipath fading), we added a Moving Average of RSSI feature to smoothen the sudden variations in data.

In [15]:

```
def moving_average(inp):
  moving_avg=list(inp["RSSI(dBm)"][:4])
  i = 0
  window_size=50
  while i < len(list(inp["RSSI(dBm)"])) - window_size + 1:
      this_window = list(inp["RSSI(dBm)"][i : i + window_size])
      window_average = sum(this_window) / window_size
      moving_avg.append(window_average)
      i += 1
  for z in range(len(list(inp["RSSI(dBm)"]))-len(moving_avg)):
    moving_avg.append(moving_avg[-1])
  return moving_avg
```

In [16]:

```
train_semi['Distance'] = train_semi.apply(lambda row: euclidean_dist(row['Latitude_OP'],ro
w['Longitude_OP'],row['Latitude_AP'],row['Longitude_AP'],row['Hight Difference(m)']),axis=
1)
test_semi['Distance'] = test_semi.apply(lambda row: euclidean_dist(row['Latitude_OP'],row[
'Longitude_OP'],row['Latitude_AP'],row['Longitude_AP'],row['Hight Difference(m)']),axis=1)
```

In [17]:

```
train_semi = pd.concat([train_semi,pd.DataFrame(moving_average(train_semi), columns = ['M
oving Average (RSSI)'])], axis=1)
test_semi = pd.concat([test_semi,pd.DataFrame(moving_average(test_semi), columns = ['Movi
ng Average (RSSI)'])], axis=1)
```

In [18]:

```
final_train = train_semi.copy()
final_test = test_semi.copy()
```

In [19]:

```
train_semi.drop_duplicates(subset=['TimeStamp(UNIX)','Latitude_OP','Longitude_OP','RSSI(dB
m)'])
```

Out[19]:

	TimeStamp(UNIX)	Latitude_OP	Longitude_OP	SSID	Channel	RSSI(dBm)	Latitude_AP	Longitude_AP	Hight Difference(m)	Out
0	1631687696	35.157140	136.926306	1	11	-41	35.157320	136.926447	0.0	
1	1631687697	35.157140	136.926306	1	11	-41	35.157320	136.926447	0.0	
2	1631687698	35.157140	136.926306	1	11	-41	35.157320	136.926447	0.0	
3	1631687699	35.157140	136.926306	1	11	-41	35.157320	136.926447	0.0	
4	1631687700	35.157140	136.926306	1	11	-41	35.157320	136.926447	0.0	
...	...	...	...	...	...	...	...	...	...	
1071	1631688759	35.157236	136.926489	4	1	-52	35.157165	136.926470	0.0	
1072	1631688760	35.157236	136.926489	4	1	-52	35.157165	136.926470	0.0	
1073	1631688761	35.157236	136.926489	4	1	-52	35.157165	136.926470	0.0	
1074	1631688762	35.157236	136.926489	4	1	-52	35.157165	136.926470	0.0	
1075	1631688763	35.157236	136.926489	4	1	-52	35.157165	136.926470	0.0	

1059 rows × 12 columns

In [20]:

```
train["RSSI_AAA001"] = np.where(train['SSID'] == 1, train["RSSI(dBm)"], "")
train["RSSI_AAA002"] = np.where(train['SSID'] == 2, train["RSSI(dBm)"], "")
train["RSSI_AAA003"] = np.where(train['SSID'] == 3, train["RSSI(dBm)"], "")
train["RSSI_AAA004"] = np.where(train['SSID'] == 4, train["RSSI(dBm)"], "")
```

In [21]:

```
train.drop(['SSID','RSSI(dBm)'],axis=1,inplace=True)
```

In [22]:

```
train_semi = pd.concat([train_semi,pd.get_dummies(train_semi['SSID'])], axis=1, join='inn
er').drop(columns=['SSID'])
test_semi = pd.concat([test_semi,pd.get_dummies(test_semi['SSID'])], axis=1, join='inner'
).drop(columns=['SSID'])
```

Data restructuring:

Data restructuring is an essential step of data preprocessing. We are changing the structure of the data provided to us by creating a combination of AP and RP features, to suit model training.

In [23]:

```
train_semi
```

Out[23]:

	TimeStamp(UNIX)	Latitude_OP	Longitude_OP	Channel	RSSI(dBm)	Latitude_AP	Longitude_AP	Hight Difference(m)	Outdoor
0	1631687696	35.157140	136.926306	11	-41	35.157320	136.926447	0.0	1
1	1631687697	35.157140	136.926306	11	-41	35.157320	136.926447	0.0	1
2	1631687698	35.157140	136.926306	11	-41	35.157320	136.926447	0.0	1
3	1631687699	35.157140	136.926306	11	-41	35.157320	136.926447	0.0	1
4	1631687700	35.157140	136.926306	11	-41	35.157320	136.926447	0.0	1
...	...	...	...	...	...	...	...	...	...
1071	1631688759	35.157236	136.926489	1	-52	35.157165	136.926470	0.0	1
1072	1631688760	35.157236	136.926489	1	-52	35.157165	136.926470	0.0	1
1073	1631688761	35.157236	136.926489	1	-52	35.157165	136.926470	0.0	1
1074	1631688762	35.157236	136.926489	1	-52	35.157165	136.926470	0.0	1
1075	1631688763	35.157236	136.926489	1	-52	35.157165	136.926470	0.0	1

1076 rows × 15 columns

In [24]:

```
test_semi
```

Out[24]:

	TimeStamp(UNIX)	Latitude_OP	Longitude_OP	Channel	RSSI(dBm)	Latitude_AP	Longitude_AP	Hight Difference(m)	Outdoor
0	1631689137	35.157261	136.926465	11	-41	35.157320	136.926447	0.0	1
1	1631689138	35.157261	136.926465	11	-41	35.157320	136.926447	0.0	1
2	1631689139	35.157261	136.926465	11	-41	35.157320	136.926447	0.0	1
3	1631689140	35.157261	136.926465	11	-41	35.157320	136.926447	0.0	1
4	1631689141	35.157261	136.926465	11	-41	35.157320	136.926447	0.0	1
...	...	...	...	...	...	...	...	...	...
1096	1631691288	35.157298	136.926575	1	-59	35.157165	136.926470	0.0	1
1097	1631691289	35.157298	136.926575	1	-59	35.157165	136.926470	0.0	1
1098	1631691290	35.157298	136.926575	1	-59	35.157165	136.926470	0.0	1
1099	1631691291	35.157298	136.926575	1	-59	35.157165	136.926470	0.0	1
1100	1631691292	35.157298	136.926575	1	-59	35.157165	136.926470	0.0	1

1101 rows × 15 columns

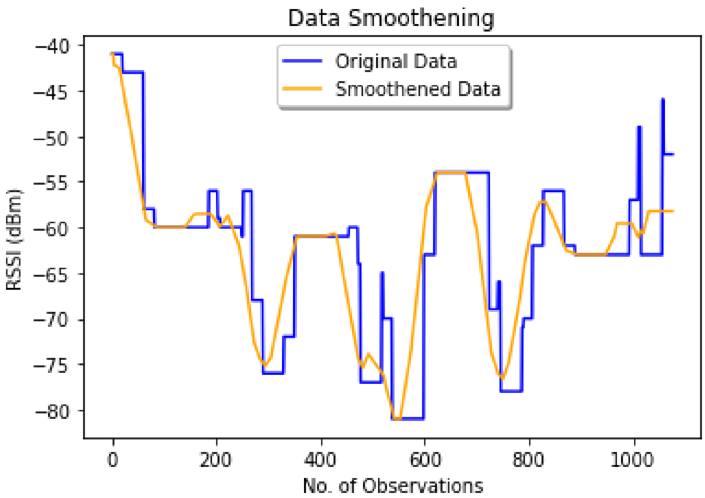
Data Smoothening:

Smoothening of the data is required as the RSSI values tend to change abruptly over time.

Various techniques for smoothening exists - in our case we are employing the simple moving averaging technique of RSSI values to undertake data smoothening.

In [25]:

```
lRSSI=list(train_semi['RSSI(dBm)'])
lMoving_avg=list(train_semi['Moving Average (RSSI)'])
plt.plot(lRSSI, color="blue", label="Original Data")
plt.plot(lMoving_avg, color="orange", label="Smoothened Data")
plt.title("Data Smoothening")
plt.xlabel("No. of Observations")
plt.ylabel("RSSI (dBm)")
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```

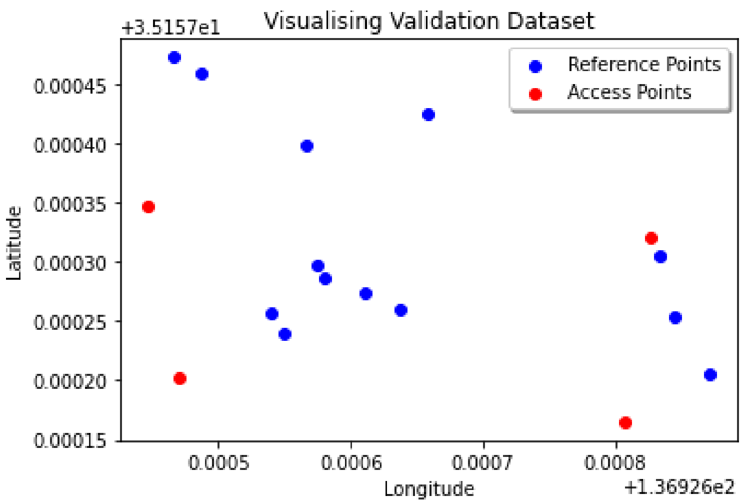


Visualising the Data Points:

Plotting the Reference Points and the Access Points given in the dataset.

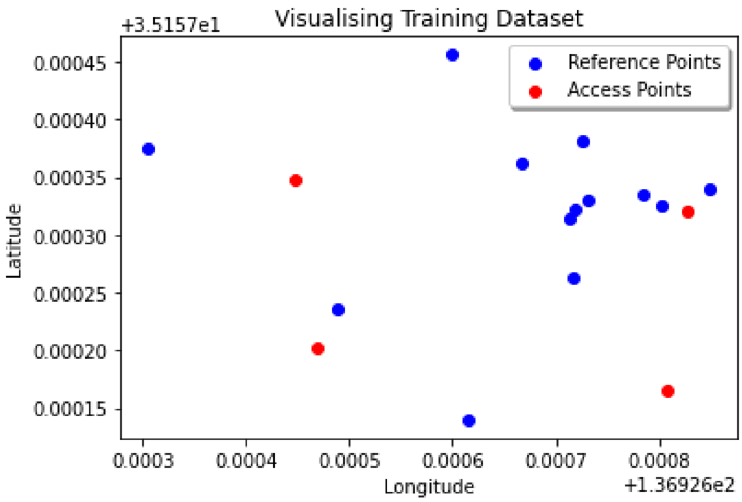
In [26]:

```
lat_RP = set(test_semi['Latitude_OP'])
long_RP = set(test_semi['Longitude_OP'])
lat_AP = set(test_semi['Latitude_AP'])
long_AP = set(test_semi['Longitude_AP'])
plt.scatter(x=list(long_RP),y=list(lat_RP), color="blue", label="Reference Points")
plt.scatter(x=list(long_AP),y=list(lat_AP), color="red", label="Access Points")
plt.title("Visualising Validation Dataset")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```



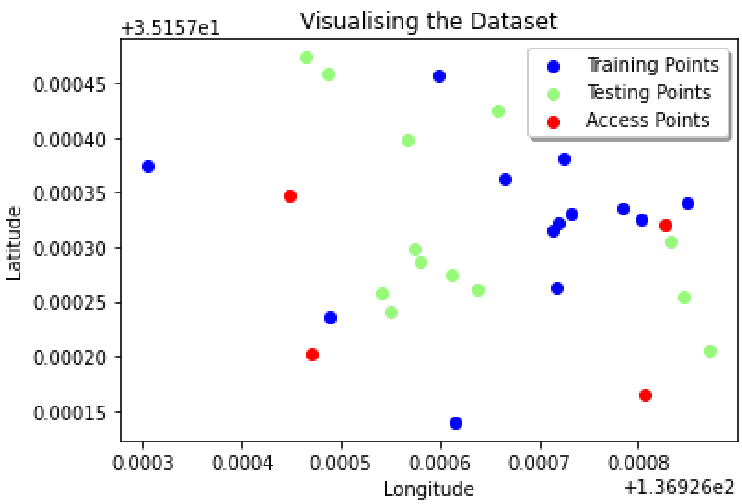
In [27]:

```
lat_RP = set(train_semi['Latitude_OP'])
long_RP = set(train_semi['Longitude_OP'])
lat_AP = set(train_semi['Latitude_AP'])
long_AP = set(train_semi['Longitude_AP'])
plt.scatter(x=list(long_RP),y=list(lat_RP), color="blue", label="Reference Points")
plt.scatter(x=list(long_AP),y=list(lat_AP), color="red", label="Access Points")
plt.title("Visualising Training Dataset")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```



In [28]:

```
lat_RP_tr = set(train_semi['Latitude_OP'])
long_RP_tr = set(train_semi['Longitude_OP'])
lat_AP_tr = set(train_semi['Latitude_AP'])
long_AP_tr = set(train_semi['Longitude_AP'])
lat_RP_te = set(test_semi['Latitude_OP'])
long_RP_te = set(test_semi['Longitude_OP'])
lat_AP_te = set(test_semi['Latitude_AP'])
long_AP_te = set(test_semi['Longitude_AP'])
plt.scatter(x=list(long_RP_tr),y=list(lat_RP_tr), color="blue", label="Training Points")
plt.scatter(x=list(long_RP_te),y=list(lat_RP_te), color='xkcd:light green', label="Testin
g Points")
plt.scatter(x=list(long_AP),y=list(lat_AP), color="red", label="Access Points")
plt.title("Visualising the Dataset")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```



Models

At first, we create a Baseline Model using mathematical relationship between distance and RSSI. This model and its results will serve as reference for other ML model's performance

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Baseline Model

In [29]:

```
test_semi['Baseline Dist'] = 10.43*(10**((-61-test_semi['RSSI(dBm)'])/27))
test_semi['Baseline Dist'].values[test_semi['Baseline Dist'].values>test_semi['Distance'].
max()]=test_semi['Distance'].max()
```

Results of Baseline Model:

In [30]:

```
dist_err=((test_semi['Distance']-test_semi['Baseline Dist'])**2)**0.5
df_error = pd.DataFrame(dist_err, columns = ['Distance Error'])
print("MEAN DISTANCE ERROR USING BASELINE MODEL :", dist_err.mean(),'m')
print("MAXIMUM DISTANCE ERROR USING BASELINE MODEL :", dist_err.max(),'m')
```

```
MEAN DISTANCE ERROR USING BASELINE MODEL : 12.131676973077862 m
MAXIMUM DISTANCE ERROR USING BASELINE MODEL : 32.460504981009464 m
```

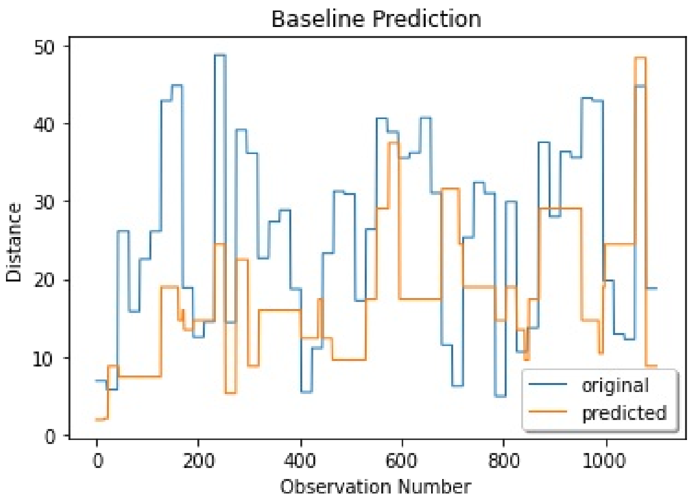
In [31]:

```
count = len([i for i in dist_err if i  < 2])
low_error = count / len(dist_err) * 100
print("Percentage of data with less than 2m error : ",low_error,"%")
```

```
Percentage of data with less than 2m error :  7.629427792915531 %
```

In [32]:

```
x_ax = range(len(test_semi['Baseline Dist']))
plt.plot(x_ax, test_semi['Distance'], linewidth=1, label="original")
plt.plot(x_ax, test_semi['Baseline Dist'], linewidth=1.1, label="predicted")
plt.title("Baseline Prediction")
plt.xlabel('Observation Number')
plt.ylabel('Distance')
plt.legend(loc='best',fancybox=True, shadow=True)
# plt.grid(True)
plt.show()
```



For Machine Learning model development we follow two main concepts

1. **RSSI Distance Estimation**
2. **RSSI Fingerprinting**

1. RSSI Distance Estimation (Multilateration)

RSSI distance estimation is solely dependent on a clear correlation between distance and RSSI value. As mentioned previously clear correlation is not present, thereby giving us considerable distance error between the

predicted location and actual location.

For performing the same we have tried several algorithms, the following have yielded the best results:

Linear Regression using Polynomial Features of Degree 2:

Since from the formula of RSSI and distance :

where n=2, an inverse square law exists between RSSI and distance, thereby motivating us to use the same.

The following illustrate the results obtained:

In [33]:

```
trainX_final = train_semi[['Latitude_AP', 'Longitude_AP', 'Channel', 'RSSI(dBm)', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)', 1, 2, 3, 4]]
trainY_final = train_semi[['Latitude_OP','Longitude_OP','Distance']]
testX_final = test_semi[['Latitude_AP', 'Longitude_AP', 'Channel', 'RSSI(dBm)', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)', 1, 2, 3, 4]]
testY_final = test_semi[['Latitude_OP','Longitude_OP','Distance']]
mm_scaler = MinMaxScaler()
train_X = pd.DataFrame(mm_scaler.fit_transform(trainX_final),columns=['Latitude_AP', 'Longitude_AP', 'Channel', 'RSSI(dBm)', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)', '1', '2', '3', '4'])
test_X = pd.DataFrame(mm_scaler.transform(testX_final),columns=['Latitude_AP', 'Longitude_AP', 'Channel', 'RSSI(dBm)', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)', '1', '2', '3', '4'])
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1679: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1679: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1679: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
  FutureWarning,
```

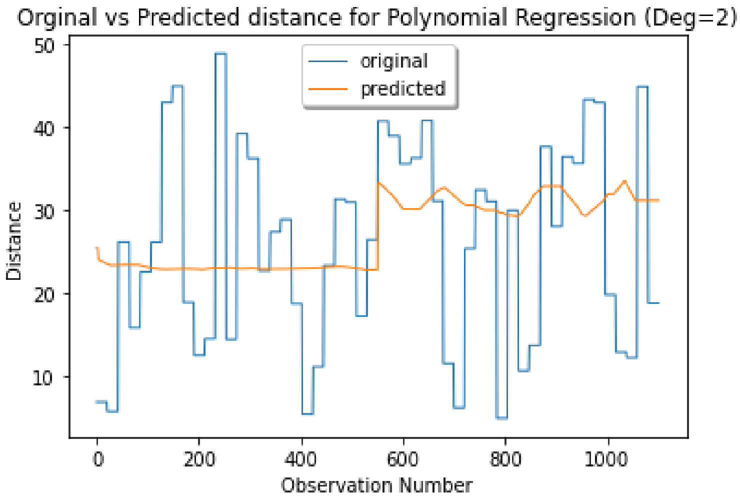
Estimation of Distance of RP from AP using Linear Regression with Polynomial Feature of Degree 2

In [34]:

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

polyfeat = PolynomialFeatures(degree=2)
newtrain_X = polyfeat.fit_transform(train_X[['Channel', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)']])
newtest_X = polyfeat.transform(test_X[['Channel', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)']])

model1 = LinearRegression(normalize=True, fit_intercept=False)
model1.fit(newtrain_X, trainY_final['Distance'])
pred_y = model1.predict(newtest_X)

dist_err=((testY_final['Distance']-pred_y)**2)**0.5
df_error = pd.DataFrame(dist_err)
df_error.clip(upper=pd.Series({'Distance': 38}), axis=1, inplace=True)

plt.plot(testY_final['Distance'], linewidth=1, label="original")
plt.plot(pred_y, linewidth=1, label="predicted")
plt.title("Orginal vs Predicted distance for Polynomial Regression (Deg=2)")
plt.xlabel('Observation Number')
plt.ylabel('Distance')
```

```
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_base.py:145: FutureWarning: '
normalize' was deprecated in version 1.0 and will be removed in 1.2.
If you wish to scale the data, use Pipeline with a StandardScaler in a preprocessing stage
. To reproduce the previous behavior:

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), LinearRegression())

If you wish to pass a sample_weight parameter, you need to pass it as a fit parameter to e
ach step of the pipeline as follows:

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)


  FutureWarning,
```



Results obtained are as follows:

In [35]:

```
print("MEAN DISTANCE ERROR USING POLYNOMIAL REGRESSOR (DEGREE 2): ", df_error['Distance'].
mean(),"m")
print("MAXIMUM DISTANCE ERROR USING POLYNOMIAL REGRESSOR(DEGREE 2): ", df_error['Distance'
].max(),"m")
```

```
MEAN DISTANCE ERROR USING POLYNOMIAL REGRESSOR (DEGREE 2):  10.0736354919281 m
MAXIMUM DISTANCE ERROR USING POLYNOMIAL REGRESSOR(DEGREE 2):  25.791606937720367 m
```

In [36]:

```
count = len([i for i in df_error['Distance'] if i  < 2])
low_error = count / len(df_error['Distance']) * 100
print("Percentage of data with less than 2m error : ",low_error,"%")
```

```
Percentage of data with less than 2m error :  11.807447774750226 %
```

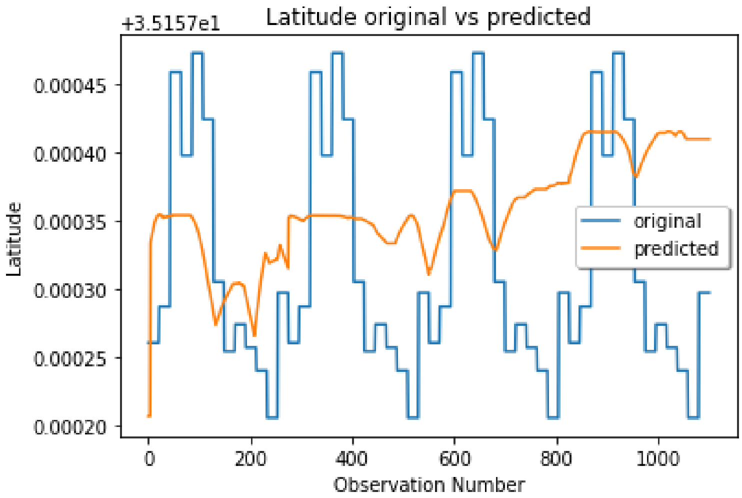
Estimation of Latitude and Longitude using Linear Regression with Polynomial Feature of Degree 2

In [37]:

```
polyfeat = PolynomialFeatures(degree=2)
newtrain_X = polyfeat.fit_transform(train_X[['Latitude_AP','Longitude_AP','Channel', 'High
t Difference(m)', 'Outdoor', 'Moving Average (RSSI)','1','2','3','4']])
newtest_X = polyfeat.transform(test_X[['Latitude_AP','Longitude_AP','Channel', 'Hight Diff
erence(m)', 'Outdoor', 'Moving Average (RSSI)','1','2','3','4']])

model2 = LinearRegression(normalize=True, fit_intercept=False)
```

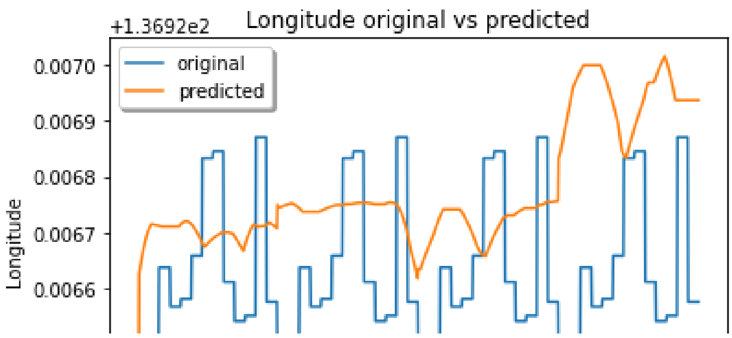
```
model2.fit(newtrain_X, trainY_final[['Latitude_OP','Longitude_OP']])
pred_y = model2.predict(newtest_X)

pred = pd.DataFrame(pred_y, columns = ['Latitude','Longitude'])
pred['dist_err'] = (((pred['Latitude']-testY_final['Latitude_OP'])*111000)**2 + (((pred['
Longitude']-testY_final['Longitude_OP'])*111000)**2))**0.5
pred.clip(upper=pd.Series({'dist_err': 38}), axis=1,inplace=True)

plt.plot(testY_final[['Latitude_OP']],label="original")
plt.plot(pred_y[:,0],label="predicted")
plt.title("Latitude original vs predicted")
plt.xlabel("Observation Number")
plt.ylabel("Latitude")
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```

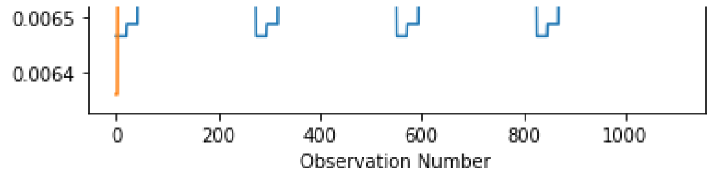
```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_base.py:145: FutureWarning: '
normalize' was deprecated in version 1.0 and will be removed in 1.2.
If you wish to scale the data, use Pipeline with a StandardScaler in a preprocessing stage
. To reproduce the previous behavior:

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), LinearRegression())

If you wish to pass a sample_weight parameter, you need to pass it as a fit parameter to e
ach step of the pipeline as follows:

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)


  FutureWarning,
```



In [38]:

```
plt.plot(testY_final[['Longitude_OP']],label="original")
plt.plot(pred_y[:,1],label="predicted")
plt.title("Longitude original vs predicted")
plt.xlabel("Observation Number")
plt.ylabel("Longitude")
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```





Results Obtained

In [39]:

```
print("MEAN DISTANCE ERROR USING POLYNOMIAL REGRESSOR (DEGREE 2): ", pred['dist_err'].mean
(),"m")
print("MAXIMUM DISTANCE ERROR USING POLYNOMIAL REGRESSOR(DEGREE 2): ", pred['dist_err'].ma
x(),"m")
```

```
MEAN DISTANCE ERROR USING POLYNOMIAL REGRESSOR (DEGREE 2):  22.529960865882906 m
MAXIMUM DISTANCE ERROR USING POLYNOMIAL REGRESSOR(DEGREE 2):  38.0 m
```

In [40]:

```
count = len([i for i in pred['dist_err'] if i  < 2])
low_error = count / len(pred['dist_err']) * 100
print("Percentage of data with less than 2m error : ",low_error,"%")
```

```
Percentage of data with less than 2m error :  0.0 %
```

AdaBoost

As Adaptive Boosting follows an ensemble approach it significantly improves the results from Linear Regressor, thus motivating us to put it to use.

We created 4 models each for each AP estimating the distance of the RP from the AP.

Distance Estimation using AdaBoost

In [41]:

```
from sklearn.ensemble import AdaBoostRegressor
from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import mean_squared_error

mm_scaler = MinMaxScaler()
train_semiX = pd.DataFrame(mm_scaler.fit_transform(train_semi[['Latitude_AP', 'Longitude_A
P', 'Channel', 'RSSI(dBm)', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)', 1,
2, 3, 4]]),columns=['Latitude_AP', 'Longitude_AP', 'Channel', 'RSSI(dBm)', 'Hight Differe
nce(m)', 'Outdoor', 'Moving Average (RSSI)', 1, 2, 3, 4])
test_semiX = pd.DataFrame(mm_scaler.transform(test_semi[['Latitude_AP', 'Longitude_AP', 'C
hannel', 'RSSI(dBm)', 'Hight Difference(m)', 'Outdoor', 'Moving Average (RSSI)', 1, 2, 3,
4]]),columns=['Latitude_AP', 'Longitude_AP', 'Channel', 'RSSI(dBm)', 'Hight Difference(m)'
, 'Outdoor', 'Moving Average (RSSI)', 1, 2, 3, 4])

ap01_dat_tr = pd.concat([train_semiX[train_semiX[1]==1],(train_semi[train_semi[1]==1])[['
Distance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
ap02_dat_tr = pd.concat([train_semiX[train_semiX[2]==1],(train_semi[train_semi[2]==1])[['
Distance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
ap03_dat_tr = pd.concat([train_semiX[train_semiX[3]==1],(train_semi[train_semi[3]==1])[['
Distance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
ap04_dat_tr = pd.concat([train_semiX[train_semiX[4]==1],(train_semi[train_semi[4]==1])[['
Distance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
ap01_dat_te = pd.concat([test_semiX[test_semiX[1]==1],(test_semi[test_semi[1]==1])[['Dist
ance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
ap02_dat_te = pd.concat([test_semiX[test_semiX[2]==1],(test_semi[test_semi[2]==1])[['Dist
ance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
ap03_dat_te = pd.concat([test_semiX[test_semiX[3]==1],(test_semi[test_semi[3]==1])[['Dist
ance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
ap04_dat_te = pd.concat([test_semiX[test_semiX[4]==1],(test_semi[test_semi[4]==1])[['Dist
ance','Latitude_OP','Longitude_OP']]],axis=1).reset_index(drop=True)
```

```
ap01_datX_tr = ap01_dat_tr[['Outdoor','Moving Average (RSSI)']]
ap01_datY_tr = ap01_dat_tr[['Distance']]
ap02_datX_tr = ap02_dat_tr[['Outdoor','Moving Average (RSSI)']]
ap02_datY_tr = ap02_dat_tr[['Distance']]
ap03_datX_tr = ap03_dat_tr[['Outdoor','Moving Average (RSSI)']]
ap03_datY_tr = ap03_dat_tr[['Distance']]
ap04_datX_tr = ap04_dat_tr[['Outdoor','Moving Average (RSSI)']]
ap04_datY_tr = ap04_dat_tr[['Distance']]
ap01_datX_te = ap01_dat_te[['Outdoor','Moving Average (RSSI)']]
ap01_datY_te = ap01_dat_te[['Distance']]
ap02_datX_te = ap02_dat_te[['Outdoor','Moving Average (RSSI)']]
ap02_datY_te = ap02_dat_te[['Distance']]
ap03_datX_te = ap03_dat_te[['Outdoor','Moving Average (RSSI)']]
ap03_datY_te = ap03_dat_te[['Distance']]
ap04_datX_te = ap04_dat_te[['Outdoor','Moving Average (RSSI)']]
ap04_datY_te = ap04_dat_te[['Distance']]
polyfeat = PolynomialFeatures(degree=2)
ap01_datX_tr = polyfeat.fit_transform(ap01_datX_tr)
ap01_datX_te = polyfeat.transform(ap01_datX_te)
polyfeat = PolynomialFeatures(degree=2)
ap02_datX_tr = polyfeat.fit_transform(ap02_datX_tr)
ap02_datX_te = polyfeat.transform(ap02_datX_te)
polyfeat = PolynomialFeatures(degree=2)
ap03_datX_tr = polyfeat.fit_transform(ap03_datX_tr)
ap03_datX_te = polyfeat.transform(ap03_datX_te)
polyfeat = PolynomialFeatures(degree=2)
ap04_datX_tr = polyfeat.fit_transform(ap04_datX_tr)
ap04_datX_te = polyfeat.transform(ap04_datX_te)

ada_AP1 = AdaBoostRegressor(n_estimators=50)
ada_AP1.fit(ap01_datX_tr,ap01_datY_tr)
prediction = ada_AP1.predict(ap01_datX_te)
prediction = prediction.reshape(-1,1)

total_dist_err = []
dist=[]
dist=dist+list(prediction[:,0])

dist_err=((ap01_datY_te-prediction)**2)**0.5
df_error = pd.DataFrame(dist_err, columns = ['Distance Error'])
dist_err.clip(upper=pd.Series({'Distance': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)

ada_AP2 = AdaBoostRegressor(n_estimators=50)
ada_AP2.fit(ap02_datX_tr,ap02_datY_tr)
prediction = ada_AP2.predict(ap02_datX_te)
prediction = prediction.reshape(-1,1)

dist=dist+list(prediction)
dist_err=((ap02_datY_te-prediction)**2)**0.5
df_error = pd.DataFrame(dist_err, columns = ['Distance Error'])
dist_err.clip(upper=pd.Series({'Distance': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)

ada_AP3 = AdaBoostRegressor(n_estimators=50)
ada_AP3.fit(ap03_datX_tr,ap03_datY_tr)
prediction = ada_AP3.predict(ap03_datX_te)
prediction = prediction.reshape(-1,1)

dist=dist+list(prediction[:,0])
dist_err=((ap03_datY_te-prediction)**2)**0.5
df_error = pd.DataFrame(dist_err, columns = ['Distance Error'])
dist_err.clip(upper=pd.Series({'Distance': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)

ada_AP4 = AdaBoostRegressor(n_estimators=50)
ada_AP4.fit(ap04_datX_tr,ap04_datY_tr)
prediction = ada_AP4.predict(ap04_datX_te)
prediction = prediction.reshape(-1,1)

dist=dist+list(prediction[:,0])
dist_err=((ap04_datY_te-prediction)**2)**0.5
```

```
df_error = pd.DataFrame(dist_err, columns = ['Distance Error'])
dist_err.clip(upper=pd.Series({'Distance': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1679: FutureWarning: Fe
ature names only support names that are all strings. Got feature names with dtypes: ['int'
, 'str']. An error will be raised in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1679: FutureWarning: Fe
ature names only support names that are all strings. Got feature names with dtypes: ['int'
, 'str']. An error will be raised in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1679: FutureWarning: Fe
ature names only support names that are all strings. Got feature names with dtypes: ['int'
, 'str']. An error will be raised in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:985: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of
y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:985: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of
y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:985: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of
y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:985: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of
y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

Results obtained

In [42]:

```
adamean=sum(total_dist_err)/len(total_dist_err)
adamax=max(total_dist_err)
print("MEAN DISTANCE ERROR USING ADABOOST REGRESSOR: ", adamean[0],'m')
print("MAXIMUM DISTANCE ERROR USING ADABOOST REGRESSOR: ",adamax[0],'m')
```

```
MEAN DISTANCE ERROR USING ADABOOST REGRESSOR:  14.175428476665237 m
MAXIMUM DISTANCE ERROR USING ADABOOST REGRESSOR:  34.413591805764185 m
```

In [43]:

```
count = len([i for i in total_dist_err if i  < 2])
low_error = count / len(total_dist_err) * 100
print("Percentage of data with less than 2m error : ",low_error,'%')
```

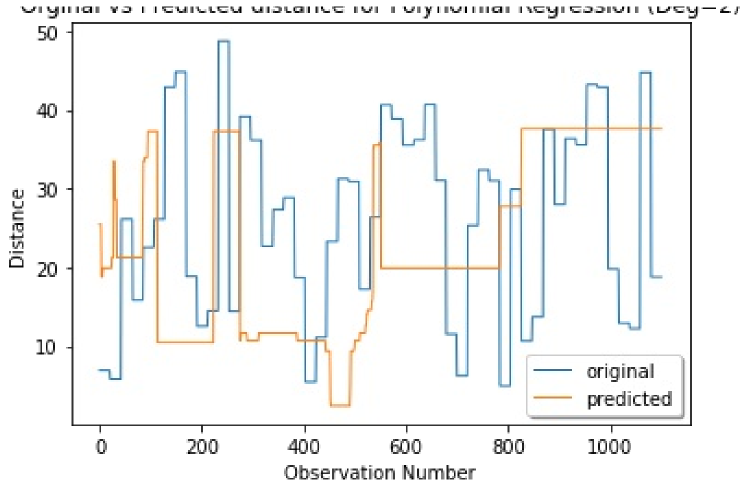
```
Percentage of data with less than 2m error :  5.812897366030881 %
```

In [44]:

```
x_ax = range(len(dist))
plt.plot(x_ax, testY_final['Distance'], linewidth=1, label="original")
plt.plot(x_ax, dist, linewidth=1, label="predicted")
plt.title("Orginal vs Predicted distance for Polynomial Regression (Deg=2)")
plt.ylabel('Distance')
plt.xlabel('Observation Number')
plt.legend(loc='best',fancybox=True, shadow=True)
# plt.grid(True)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:136: VisibleDeprecationWarni
ng: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or
-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do th
is, you must specify 'dtype=object' when creating the ndarray
  return array(a, dtype, copy=False, order=order, subok=True)
```

Orginal vs Predicted distance for Polynomial Regression (Deg=2)



Direct estimation of Latitude and Longitude using AdaBoost

In this case we trained 8 different models for the 4 different APs. Two models for each AP for predicting Latitude and Longitude of the reference points/observation points respectively.

In [45]:

```
ap01_datX_tr = ap01_dat_tr[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap01_datY_tr = ap01_dat_tr[['Latitude_OP','Longitude_OP']]
ap02_datX_tr = ap02_dat_tr[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap02_datY_tr = ap02_dat_tr[['Latitude_OP','Longitude_OP']]
ap03_datX_tr = ap03_dat_tr[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap03_datY_tr = ap03_dat_tr[['Latitude_OP','Longitude_OP']]
ap04_datX_tr = ap04_dat_tr[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap04_datY_tr = ap04_dat_tr[['Latitude_OP','Longitude_OP']]
ap01_datX_te = ap01_dat_te[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap01_datY_te = ap01_dat_te[['Latitude_OP','Longitude_OP']]
ap02_datX_te = ap02_dat_te[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap02_datY_te = ap02_dat_te[['Latitude_OP','Longitude_OP']]
ap03_datX_te = ap03_dat_te[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap03_datY_te = ap03_dat_te[['Latitude_OP','Longitude_OP']]
ap04_datX_te = ap04_dat_te[['Latitude_AP','Longitude_AP','Outdoor','Moving Average (RSSI)'
]]
ap04_datY_te = ap04_dat_te[['Latitude_OP','Longitude_OP']]

ada_AP1_Lat = AdaBoostRegressor(n_estimators=25)
ada_AP1_Lat.fit(ap01_datX_tr,ap01_datY_tr['Latitude_OP'])
prediction1_Lat = ada_AP1_Lat.predict(ap01_datX_te)
prediction1_Lat = pd.DataFrame(prediction1_Lat.reshape(-1,1),columns=['Latitude'])
ada_AP1_Lon = AdaBoostRegressor(n_estimators=25)
ada_AP1_Lon.fit(ap01_datX_tr,ap01_datY_tr['Longitude_OP'])
prediction1_Lon = ada_AP1_Lon.predict(ap01_datX_te)
prediction1_Lon = pd.DataFrame(prediction1_Lon.reshape(-1,1),columns=['Longitude'])

total_dist_err = []
pred1 = pd.concat([prediction1_Lat,prediction1_Lon],axis=1)
pred['dist_err'] = (((pred1['Latitude']-ap01_datY_tr['Latitude_OP'])*111000)**2 + (((pred
1['Longitude']-ap01_datY_tr['Longitude_OP'])*111000)**2))**0.5
pred.clip(upper=pd.Series({'dist_err': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)

ada_AP2_Lat = AdaBoostRegressor(n_estimators=25)
ada_AP2_Lat.fit(ap02_datX_tr,ap02_datY_tr['Latitude_OP'])
prediction2_Lat = ada_AP2_Lat.predict(ap02_datX_te)
prediction2_Lat = pd.DataFrame(prediction2_Lat.reshape(-1,1),columns=['Latitude'])
ada_AP2_Lon = AdaBoostRegressor(n_estimators=25)
```

```
ada_AP2_Lon.fit(ap02_datX_tr,ap01_datY_tr['Longitude_OP'])
prediction2_Lon = ada_AP2_Lon.predict(ap02_datX_te)
prediction2_Lon = pd.DataFrame(prediction2_Lon.reshape(-1,1),columns=['Longitude'])

pred2 = pd.concat([prediction2_Lat,prediction2_Lon],axis=1)
pred['dist_err'] = (((pred2['Latitude']-ap02_datY_tr['Latitude_OP'])*111000)**2 + (((pred
2['Longitude']-ap02_datY_tr['Longitude_OP'])*111000)**2))**0.5
pred.clip(upper=pd.Series({'dist_err': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)

ada_AP3_Lat = AdaBoostRegressor(n_estimators=25)
ada_AP3_Lat.fit(ap03_datX_tr,ap03_datY_tr['Latitude_OP'])
prediction3_Lat = ada_AP3_Lat.predict(ap03_datX_te)
prediction3_Lat = pd.DataFrame(prediction3_Lat.reshape(-1,1),columns=['Latitude'])
ada_AP3_Lon = AdaBoostRegressor(n_estimators=25)
ada_AP3_Lon.fit(ap03_datX_tr,ap03_datY_tr['Longitude_OP'])
prediction3_Lon = ada_AP3_Lon.predict(ap03_datX_te)
prediction3_Lon = pd.DataFrame(prediction3_Lon.reshape(-1,1),columns=['Longitude'])

pred3 = pd.concat([prediction3_Lat,prediction3_Lon],axis=1)
pred['dist_err'] = (((pred3['Latitude']-ap03_datY_tr['Latitude_OP'])*111000)**2 + (((pred
3['Longitude']-ap03_datY_tr['Longitude_OP'])*111000)**2))**0.5
pred.clip(upper=pd.Series({'dist_err': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)

ada_AP4_Lat = AdaBoostRegressor(n_estimators=25)
ada_AP4_Lat.fit(ap04_datX_tr,ap04_datY_tr['Latitude_OP'])
prediction4_Lat = ada_AP4_Lat.predict(ap04_datX_te)
prediction4_Lat = pd.DataFrame(prediction4_Lat.reshape(-1,1),columns=['Latitude'])
ada_AP4_Lon = AdaBoostRegressor(n_estimators=25)
ada_AP4_Lon.fit(ap04_datX_tr,ap04_datY_tr['Longitude_OP'])
prediction4_Lon = ada_AP4_Lon.predict(ap04_datX_te)
prediction4_Lon = pd.DataFrame(prediction4_Lon.reshape(-1,1),columns=['Longitude'])

pred4 = pd.concat([prediction4_Lat,prediction4_Lon],axis=1)
pred['dist_err'] = (((pred4['Latitude']-ap04_datY_tr['Latitude_OP'])*111000)**2 + (((pred
4['Longitude']-ap04_datY_tr['Longitude_OP'])*111000)**2))**0.5
pred.clip(upper=pd.Series({'dist_err': 38}), axis=1,inplace=True)
total_dist_err += list(dist_err.values)
```

Results obtained

In [46]:

```
adamean=sum(total_dist_err)/len(total_dist_err)
adamax=max(total_dist_err)
print("MEAN DISTANCE ERROR USING ADABOOST REGRESSOR: ", adamean[0],'m')
print("MAXIMUM DISTANCE ERROR USING ADABOOST REGRESSOR: ",adamax[0],'m')
```

```
MEAN DISTANCE ERROR USING ADABOOST REGRESSOR:  12.979052804546736 m
MAXIMUM DISTANCE ERROR USING ADABOOST REGRESSOR:  26.991121482947385 m
```

In [47]:

```
count = len([i for i in total_dist_err if i  < 2])
low_error = count / len(total_dist_err) * 100
print("Percentage of data with less than 2m error : ",low_error,'%')
```

```
Percentage of data with less than 2m error :  15.636363636363637 %
```

2. RSSI Fingerprinting

Fingerprinting of RSSI gives us a map of the RSSI throughout the area of inspection, it is effective for both indoor and outdoor experimental conditions. However, many data points uniformly spread throughout the area, gives the model a better understanding, which is not available in this scenario.

KNN - Regressor

We have used KNN regressor to predict reference point locations using the concept of RSSI Fingerprinting.

In [48]:

```
from sklearn import neighbors
from sklearn.metrics import mean_squared_error
from math import sqrt
import matplotlib.pyplot as plt
%matplotlib inline

rmse_val = [] #to store rmse values for different k
for K in range(13):
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K)

    model.fit(newtrain_X, trainY_final[['Latitude_OP','Longitude_OP']])  #fit the model
    pred=model.predict(newtest_X) #make prediction on test set
    error = sqrt(mean_squared_error(testY_final[['Latitude_OP','Longitude_OP']],pred)) #ca
lculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

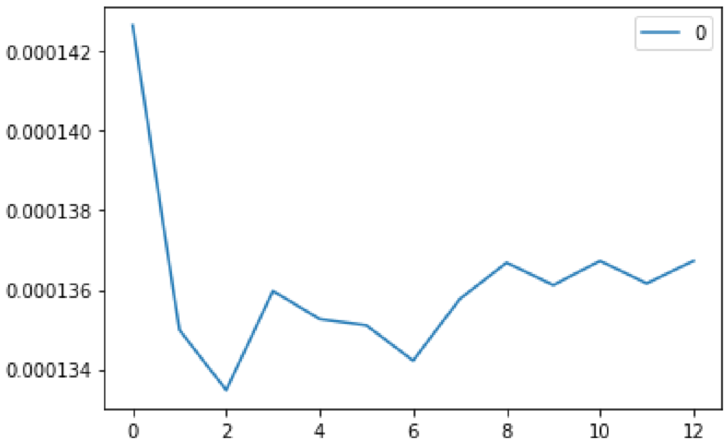
```
RMSE value for k=  1 is: 0.00014264030700196525
RMSE value for k=  2 is: 0.0001349883207070322
RMSE value for k=  3 is: 0.00013347786765541687
RMSE value for k=  4 is: 0.00013596747987660657
RMSE value for k=  5 is: 0.0001352648427235548
RMSE value for k=  6 is: 0.0001351045857036459
RMSE value for k=  7 is: 0.0001342199386390155
RMSE value for k=  8 is: 0.00013576804535908075
RMSE value for k=  9 is: 0.0001366785072172612
RMSE value for k=  10 is: 0.00013611592275921666
RMSE value for k=  11 is: 0.00013672408536584632
RMSE value for k=  12 is: 0.00013615789458791352
RMSE value for k=  13 is: 0.00013672629676039693
```

In [49]:

```
#plotting the rmse values against k values
curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

Out[49]:

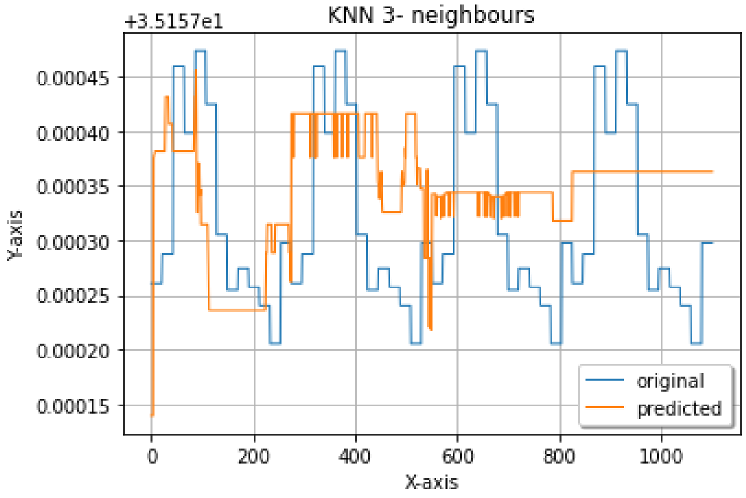
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa7457a4790>
```



In [50]:

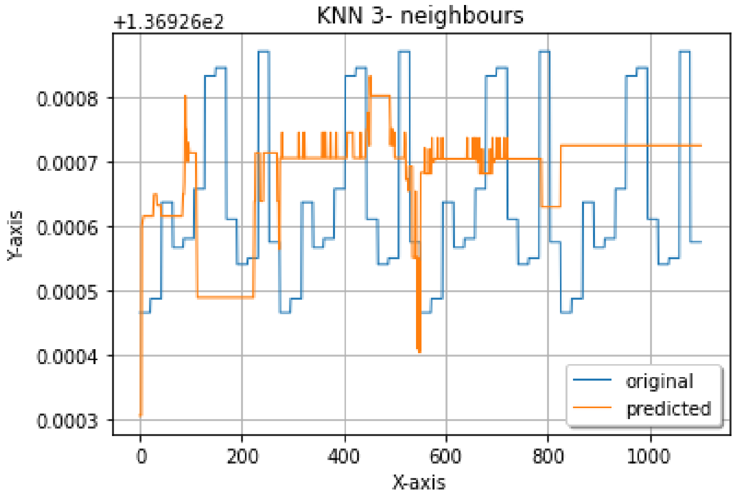
```
model = neighbors.KNeighborsRegressor(n_neighbors = 3)
model.fit(newtrain_X, trainY_final[['Latitude_OP','Longitude_OP']])  #fit the model
pred_knn=model.predict(newtest_X) #make prediction on test set

x_ax = range(len(testY_final[['Latitude_OP']]))
plt.plot(x_ax, testY_final[['Latitude_OP']], linewidth=1, label="original")
plt.plot(x_ax, pred_knn[:,0], linewidth=1.1, label="predicted")
plt.title("KNN 3- neighbours")
plt.xlabel('X-axis')
```

```
plt.ylabel('Y-axis')
plt.legend(loc='best',fancybox=True, shadow=True)
plt.grid(True)
plt.show()
```



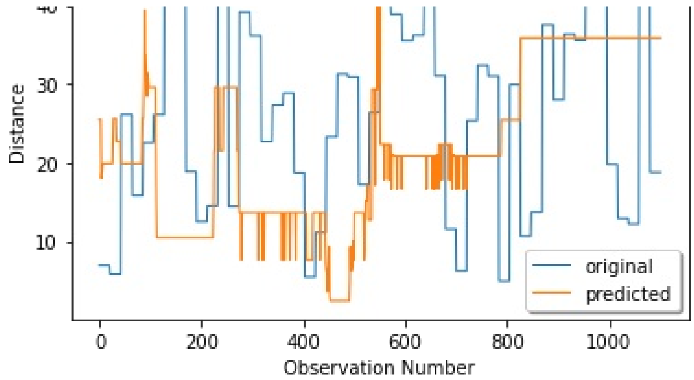
In [51]:

```
x_ax = range(len(testY_final[['Longitude_OP']]))
plt.plot(x_ax, testY_final[['Longitude_OP']], linewidth=1, label="original")
plt.plot(x_ax, pred_knn[:,1], linewidth=1.1, label="predicted")
plt.title("KNN 3- neighbours")
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
plt.legend(loc='best',fancybox=True, shadow=True)
plt.grid(True)
plt.show()
```



In [52]:

```
pred = pd.DataFrame(pred_knn, columns = ['Latitude','Longitude'])
pred['dist_err'] = (((pred['Latitude']-testY_final['Latitude_OP'])*111000)**2 + (((pred['
Longitude']-testY_final['Longitude_OP'])*111000)**2))**0.5
pred['distance'] = (((pred['Latitude']-test_semi['Latitude_AP'])*111000)**2 + (((pred['Lon
gitude']-test_semi['Longitude_AP'])*111000)**2))**0.5
x_ax = range(len(test_semi['Distance']))
plt.plot(x_ax, test_semi['Distance'], linewidth=1, label="original")
plt.plot(x_ax, pred['distance'], linewidth=1.1, label="predicted")
plt.title("Original vs Predicted distance for KNN Regressor")
plt.xlabel('Observation Number')
plt.ylabel('Distance')
plt.legend(loc='best',fancybox=True, shadow=True)
plt.show()
```



In [53]:

```
pred.clip(upper=pd.Series({'dist_err': 38}), axis=1,inplace=True)
```

Results

In [54]:

```
knnmean=pred['dist_err'].mean()
knnmax=pred['dist_err'].max()
print("MEAN DISTANCE ERROR USING KNN REGRESSOR: ", knnmean,'m')
print("MAXIMUM DISTANCE ERROR USING KNN REGRESSOR: ",knnmax,'m')
```

```
MEAN DISTANCE ERROR USING KNN REGRESSOR:  19.224908935684294 m
MAXIMUM DISTANCE ERROR USING KNN REGRESSOR:  38.0 m
```

In [55]:

```
count = len([i for i in pred['dist_err'] if i  < 2])
low_error = count / len(pred['dist_err']) * 100
print("Percentage of data with less than 2m error : ",low_error,'%')
```

```
Percentage of data with less than 2m error :  0.0 %
```

Summary

We discovered that the data set downloaded was in relatively clean state and therefore we did not have to clean up the data. However, feature engineering was required to come to the conclusions regarding the data.

Since the number of Reference point in the training dataset is limited to 13, and is not uniformly distributed over the localisation area, satisfactory results could not be obtained using RSSI fingerprinting technique.

Moreover as RSSI values at the same time instant were sometimes available to 3, sometimes to 4 - estimating the location from multilateration was not possible.

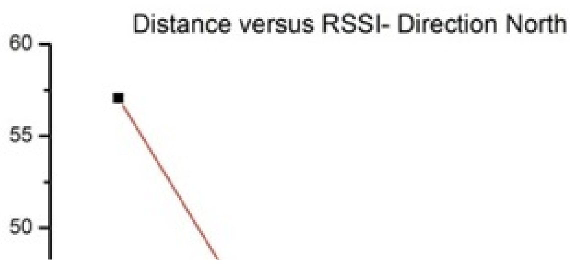
The best result was achieved using AdaBoost Regressor.

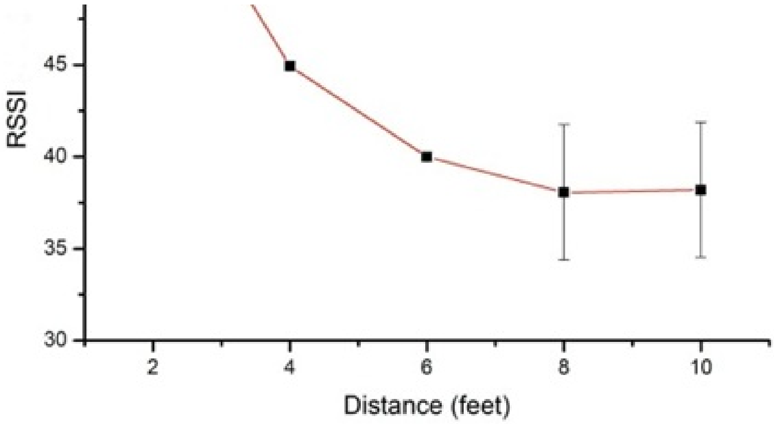
Challenges of using RSSI in Practical Scenario:

RSSI values are highly sensitive to changes in the environment and they vary rapidly, reducing its reliability.

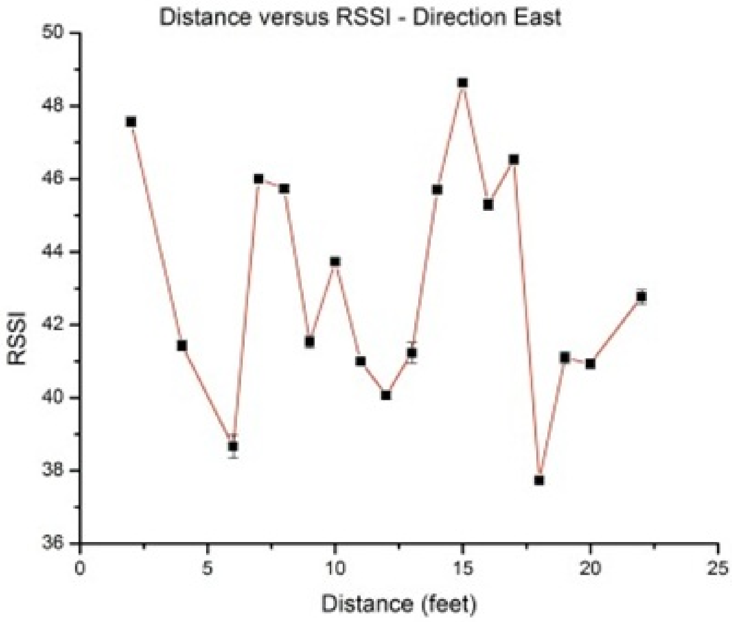
One study by Parameswaran et al. illustrates the same unreliability -

When RSSI was measured from the North of an AP the RSSI vs distance plot obtained is illustrated below:





The same AP when measuring RSSI from the east yielded this RSSI vs distance plot:



This clearly illustrates the unreliability of RSSI when using it for localization.

Future aspects for improvement

- Use of Link Quality Index, Time of Arrival and Angle of Arrival can be done instead of RSSI for more robust localiztion results, as these parameters are not so heavily influenced by the environment as RSSI.

- Filters such as Kalman Filter and Gaussian Filter can be applied to the data if the data collected is in the form of a Time-Series with changes in Latitude and Longitude.
- More number of reference points in the data provided would significantly improve the performance of the models.

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