gan_chann_mod_final

May 18, 2021

[1]:
```python
# Import tensorflow and keras modules
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Input
from tensorflow.keras.layers import LeakyReLU, BatchNormalization
from tensorflow.keras.layers import concatenate
from tensorflow.keras.optimizers import Adam, RMSprop
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import to_categorical, plot_model

# Import processing and displaying modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pickle
import os
import sys
```

[2]:
```python
# Set the main path as the DLProject folder
main_path = os.path.abspath("../")
sys.path.append(main_path)

# Import mmwchanmod module from the main path.
# mmwchanmod module is cloned from nyu-wireless
# github sites for processing the pickle file.
# https://github.com/nyu-wireless/mmwchanmod
import mmwchanmod
```

[3]:
```python
# Load the pre-processed ray tracing data
# The train_data is used to train the GAN
# and the test_data is used to generate channel
# samples and to evaluate the GAN performance.
fn = 'factory_warehouse.p'
with open(os.path.join(main_path,fn), 'rb') as fp:
    config,train_data,test_data = pickle.load(fp)

# Display the path information contained in the pickle file.
# The eight parameters are
```

```
# dvec: The dista, end =" "nce vector between the transmitter and the receiver
# link_state: The state of link: LOS, NLOS, or Outage
# los_pl: The path loss of the LOS path if it exists
# los_ang: The four angles (AOA, ZOA, AOD, ZOD) of the LOS path if it exists
# los_dly: The time delay of the LOS path if it exists
# nlos_pl: The path loss of the NLOS paths
# nlos_ang: The four angles of the NLOS paths
# nlos_dly: The time delay of the NLOS paths
# tx_pos
print(f"There are {train_data['dvec'].shape[0]} links in the train dataset.")
print("Ten path parameters:")
for key in train_data.keys():
    print(key, end =", ")
```

```
There are 1759 links in the train dataset.
Ten path parameters:
dvec, link_state, los_pl, los_ang, los_dly, nlos_pl, nlos_ang, nlos_dly, tx_pos,
rx_pos,
```

[4]:

```
# Separate the train datasets into three subsets:
# LOS, NLOS, Outage
# LOS: A boresight path exists between the TX and RX
# NLOS: The boresight path is blocked
# Outage: No paths between the TX and RX
num_link = train_data['dvec'].shape[0]
train_data['dist'] = np.zeros(num_link)
train_data['pl_omni'] = np.zeros(num_link)

# Initialize the indices of three subsets
los_index = []
nlos_index = []
outage_index = []
for link in range(num_link):
  if train_data['link_state'][link] == 1:
    los_index.append(link)
  elif train_data['link_state'][link] == 2:
    nlos_index.append(link)
  elif train_data['link_state'][link] == 0:
    outage_index.append(link)
  else:
    print(f'Unexpected link state at {link}')

  # Only use the distance and path loss values here for path loss plots
  dvec = train_data['dvec'][link]
  train_data['dist'][link] = np.sqrt(np.dot(dvec,dvec))
  los_pl = train_data['los_pl'][link]
  nlos_pl = train_data['nlos_pl'][link]
```

```
    nlos_pr_lin = np.sum(10**((0-nlos_pl)/10))
    pr_lin = 10**((0-los_pl)/10) + nlos_pr_lin
    train_data['pl_omni'][link] = 0-10*np.log10(pr_lin)
```

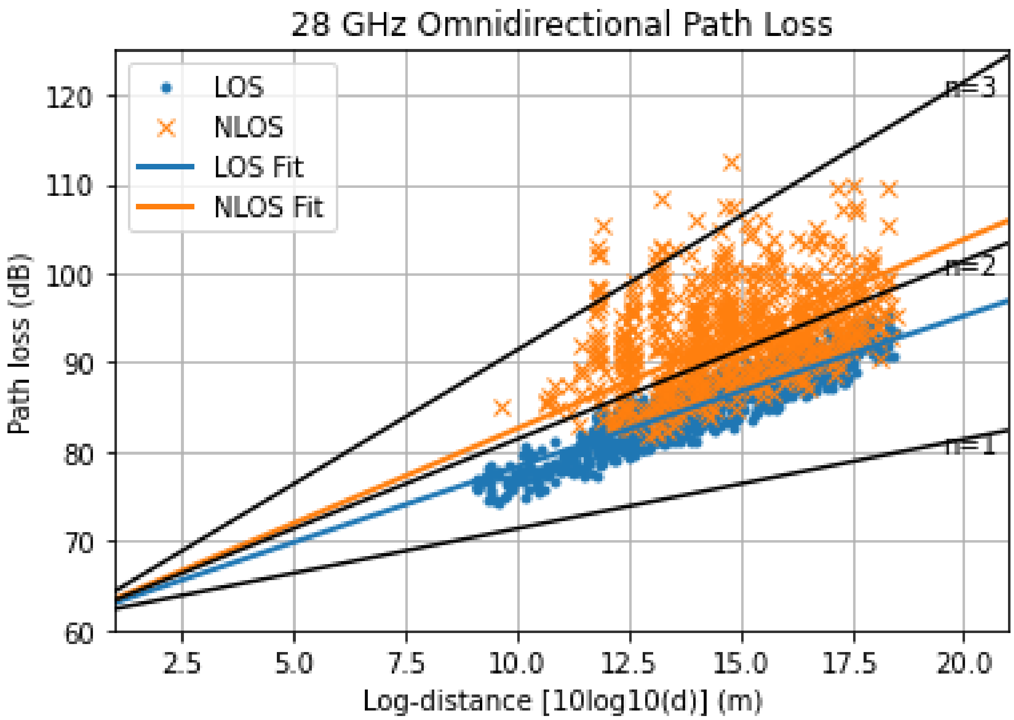
[5]:
```
# Import scipy module for scientific constants
from scipy.constants import c, pi
# Carrier frequency:28 GHz
fc = 28e9
# Wavelength
lamb = c/fc
# Anchor distance: 1 m
d0 = 1
# Free space path loss at 1 m
fspl0 = 20*np.log10(4*pi*d0*fc/c)
# The maximum number of paths per link
num_paths = 20
```

[6]:
```
def compute_ple(dist_vals, pl_vals, fc, d0):
    """
    Compute the path loss exponent (PLE) and shadow fading (SF)

    Parameters
    ----------
    dist_vals : (n,) array
        TX-RX separation distance
    pl_vals : (n,) array
        Path loss in dB scale
    fc : scalar
        Carrier frequency
    d0 : scalar
        Anchor distance

    Returns
    -------
    ple:  scalar
        PLE
    sf_std:  scalar
        Standard deviation of SF
    """
    lamb = c/fc
    fspl0 = 20*np.log10(4*pi*d0*fc/c)
    dist = 10*np.log10(dist_vals).reshape((-1,1))
    pl = pl_vals.reshape((-1,1)) - fspl0

    # Compute the optimal PLE
    ple,res_sum,_,_ = np.linalg.lstsq(dist,pl,rcond=None)
    ple = ple.item()
```

```
    # Compute the corresponding SF
    sf_std = np.sqrt(res_sum/dist.shape[0]).item()

    return ple, sf_std
```

[7]:

```
# Compute the PLE and SF for LOS and NLOS datasets
ple_los, sf_los_std = compute_ple(train_data['dist'][los_index],
                                  train_data['pl_omni'][los_index], fc, d0)

ple_nlos, sf_nlos_std = compute_ple(train_data['dist'][nlos_index],
                                  train_data['pl_omni'][nlos_index], fc, d0)

# Scatter plot for the LOS and NLOS locations
plt.plot(10*np.
 ↪log10(train_data['dist'][los_index]),train_data['pl_omni'][los_index],'.
 ↪',c='C0')
plt.plot(10*np.
 ↪log10(train_data['dist'][nlos_index]),train_data['pl_omni'][nlos_index],'x',c='C1')
plt.xlim([1,21])
plt.ylim([60,125])

# Plot the fit line for the LOS and NLOS locations
plt.plot(np.linspace(0,21,num=100),fspl0+ple_los*np.linspace(0,21,num=100),
         c='C0',lw=2)
plt.plot(np.linspace(0,21,num=100),fspl0+ple_nlos*np.linspace(0,21,num=100),
         c='C1',lw=2)
plt.legend(['LOS','NLOS','LOS Fit','NLOS Fit'])

# Plot the reference lines
plt.plot(np.linspace(0,21,num=100),fspl0+2*np.linspace(0,21,num=100),'k')
plt.plot(np.linspace(0,21,num=100),fspl0+1*np.linspace(0,21,num=100),'k')
plt.plot(np.linspace(0,21,num=100),fspl0+3*np.linspace(0,21,num=100),'k')
plt.annotate('n=1',(19.5,80))
plt.annotate('n=2',(19.5,100))
plt.annotate('n=3',(19.5,120))
plt.title('28 GHz Omnidirectional Path Loss')
plt.xlabel('Log-distance [10log10(d)] (m)')
plt.ylabel('Path loss (dB)')
plt.grid(True)
plt.show()

print(f'LOS locations - PLE:{ple_los:.2f}, SF:{sf_los_std:.2f}')
print(f'NLOS locations - PLE:{ple_nlos:.2f}, SF:{sf_nlos_std:.2f}')
```




```
LOS locations - PLE:1.69, SF:1.66
NLOS locations - PLE:2.12, SF:5.19
```

[8]:

```python
# Import the MinMaxScaler to properly scale input data
from sklearn.preprocessing import MinMaxScaler
# Define own function for scaling
def data_scaler(data_in, range):
  """
  Scale the input data and record the scaler.

  Parameters
  ----------
  data_in : (n,) array
      The data to be scaled
  range : (1,2) array
      The minimum and maximum value

  Returns
  -------
  data_out : (n,) array
      The scaled data
  scaler : object
      The scaling setting
  """
```

```
    scaler = MinMaxScaler(feature_range=range)
    data_out = scaler.fit_transform(data_in)
    return data_out, scaler
```

[9]:
```
def compute_los_dir(dvec):
    """
    Compute the LOS direction

    Parameters
    ----------
    dvec : (n,3) array
        The distances in three axis

    Returns
    -------
    aoa:  (n,) array
        Azimuth angle of arrival
    zoa:  (n,) array
        Elevation angle of arrival
    aod:  (n,) array
        Azimuth angle of departure
    zod:  (n,) array
        Elevation angle of departure
    """

    x = dvec[:,0]
    y = dvec[:,1]
    z = dvec[:,2]
    aod = np.arctan(y/x)*180/pi
    zod = np.arctan(np.linalg.norm(dvec[:,0:2])/z)*180/pi
    zoa = 180 - zod
    aoa = np.zeros_like(aod)
    for i in range(dvec.shape[0]):
      if aod[i] >= 0:
        aoa[i] = aod[i] - 180
      else:
        aoa[i] = aod[i] + 180

    return (aoa, zoa, aod, zod)
```

[10]:
```
# Define some utility functions for coordinate transform
def cart_to_sph(d):
    """
    Cartesian to spherical coordinates.

    Parameters
```

```
    ----------
    d : (n,3) array
        vector of positions

    Returns
    -------
    r:  (n,) array
        radius of each point
    phi, theta:  (n,) arrays
        azimuth and inclination angles in degrees
    """

    # Compute radius
    r = np.sqrt(np.sum(d**2,axis=1))
    r = np.maximum(r, 1e-8)

    # Compute angle of departure
    phi = np.arctan2(d[:,1], d[:,0])*180/np.pi
    theta = np.arccos(d[:,2]/r)*180/np.pi

    return r, phi, theta

def sph_to_cart(r, phi, theta):
    """
    Spherical coordinates to cartesian coordinates

    Parameters
    ----------
    r:  (n,) array
        radius of each point
    phi, theta:  (n,) arrays
        azimuth and inclination angles in degrees

    Returns
    -------
    d : (n,3) array
        vector of positions

    """

    # Convert to radians
    phi = phi*np.pi/180
    theta = theta*np.pi/180

    # Convert to cartesian
    d0 = r*np.cos(phi)*np.sin(theta)
    d1 = r*np.sin(phi)*np.sin(theta)
```

```python
    d2 = r*np.cos(theta)
    d = np.stack((d0,d1,d2), axis=-1)

    return d


def spherical_add_sub(phi0,theta0,phi1,theta1,sub=True):
    """
    Angular addition and subtraction in spherical coordinates

    For addition, we start with a vector at (phi0,theta0), then rotate by
    theta1 in the (x1,x3) plane and then by phi1 in the (x1,x2) plane.
    For subtraction, we start with a vector at (phi0,theta0), then rotate by
    -phi1 in the (x1,x2) plane and then by -theta1 in the (x1,x3) plane.


    Parameters
    ----------
    phi0, theta0 : arrays of same size
        (azimuth,inclination) angle of the initial vector in degrees
    phi1, theta1 : arrays of same size
        (azimuth,inclination) angle of the rotation
    sub:  boolean
        if true, the angles are subtracted.  otherwise, they are added

    Returns
    -------
    phi2, theta2 : arrays of same size as input
        (azimuth,inclination) angle of the rotated vector

    """


    # Convert to radians
    theta0 = np.pi/180*theta0
    theta1 = np.pi/180*theta1
    phi0 = np.pi/180*phi0
    phi1 = np.pi/180*phi1


    if sub:
        # Find unit vector in direction of (theta0,phi0)
        x1 = np.sin(theta0)*np.cos(phi0)
        x2 = np.sin(theta0)*np.sin(phi0)
        x3 = np.cos(theta0)

        # Rotate by -phi1.
```

```
        y1 =  x1*np.cos(phi1) + x2*np.sin(phi1)
        y2 = -x1*np.sin(phi1) + x2*np.cos(phi1)
        y3 = x3

        # Rotate by -theta1
        z1 =  y1*np.cos(theta1) - y3*np.sin(theta1)
        z3 =  y1*np.sin(theta1) + y3*np.cos(theta1)
        z2 = y2
        z1 = np.minimum(1, np.maximum(-1, z1))

        # Compute the angle of the transformed vector
        # we use the (z3,z2,z1) coordinate system
        phi2 = np.arctan2(z2, z3)*180/np.pi
        theta2 = np.arcsin(z1)*180/np.pi
    else:

        # Find unit vector in direction of (theta0,phi0)
        x3 = np.cos(theta0)*np.cos(phi0)
        x2 = np.cos(theta0)*np.sin(phi0)
        x1 = np.sin(theta0)


        # Rotate by theta1
        y1 =  x1*np.cos(theta1) + x3*np.sin(theta1)
        y3 = -x1*np.sin(theta1) + x3*np.cos(theta1)
        y2 = x2

        # Rotate by phi1.
        z1 =  y1*np.cos(phi1) - y2*np.sin(phi1)
        z2 =  y1*np.sin(phi1) + y2*np.cos(phi1)
        z3 = y3
        z3 = np.minimum(1, np.maximum(-1, z3))

        # Compute angles
        phi2 = np.arctan2(z2, z1)*180/np.pi
        theta2 = np.arccos(z3)*180/np.pi


    return phi2, theta2
```

[11]:
```
def dataset_scaler(dvec, nlos_info, num_paths):
    """
    Scale the dataset into proper range

    Parameters
    ----------
    dvec : (n,3) array
```

```
        The distances in three axis
    nlos_info: (n,120) array
        The six-element tuple information for 20 paths
    num_paths: scalar
        The number of paths per link

    Returns
    -------
    nlos_info_scaled:  (n,120) array
        Scaled path information
    scalar_list: list
        A list of scaler used for different link parameters
    """
    scaler_list = []

    aoa, zoa, aod, zod = compute_los_dir(dvec)

    nlos_info_scaled = np.zeros_like(nlos_info)
    # Data preprocessing
    # Power
    pl_arr = nlos_info[:,np.array(range(num_paths))*6]
    pl_scaled, pl_scaler = data_scaler(pl_arr.reshape((-1,1)),(0,1))
    nlos_info_scaled[:,np.array(range(num_paths))*6] = pl_scaled.
↪reshape(-1,num_paths)
    scaler_list.append(pl_scaler)
    # Delay
    dly_arr = nlos_info[:,np.array(range(num_paths))*6+1]
    dly_scaled, dly_scaler = data_scaler(dly_arr.reshape((-1,1)),(0,1))
    nlos_info_scaled[:,np.array(range(num_paths))*6+1] = dly_scaled.
↪reshape(-1,num_paths)
    scaler_list.append(dly_scaler)

    # Arrival angles
    aoa_arr = nlos_info[:,np.array(range(num_paths))*6+2]
    zoa_arr = nlos_info[:,np.array(range(num_paths))*6+3]

    # LOS arrival angles
    aoa = np.transpose(np.tile(aoa,[num_paths,1]))
    zoa = np.transpose(np.tile(zoa,[num_paths,1]))

    # with respect to LOS direction
    arrival_angles_rot = spherical_add_sub(aoa_arr,zoa_arr,aoa,zoa)

    aoa_arr_wl = arrival_angles_rot[0] % 360
    zoa_arr_wl = arrival_angles_rot[1] % 360

    # Departure angles
```

```
    aod_arr = nlos_info[:,np.array(range(num_paths))*6+4]
    zod_arr = nlos_info[:,np.array(range(num_paths))*6+5]

    # LOS departure angles
    aod = np.transpose(np.tile(aod,[num_paths,1]))
    zod = np.transpose(np.tile(zod,[num_paths,1]))

    # with respect to LOS direction
    depart_angles_rot = spherical_add_sub(aod_arr,zod_arr,aod,zod)

    aod_arr_wl = depart_angles_rot[0] % 360
    zod_arr_wl = depart_angles_rot[1] % 360

    # Group all link parameters into the nlos_info_scaled array
    ang_arr_wl = np.
↪concatenate((aoa_arr_wl,zoa_arr_wl,aod_arr_wl,zod_arr_wl),axis=1)
    ang_scaled, ang_scaler = data_scaler(ang_arr_wl.reshape((-1,1)),(0,1))
    ang_scaled = ang_scaled.reshape((-1,num_paths*4))
    ang_index = np.arange(4).reshape((1,-1)) + np.arange(20).reshape((-1,1))*6 + 2
    ang_index = ang_index.reshape((1,-1))[0]
    nlos_info_scaled[:,ang_index] = ang_scaled
    scaler_list.append(ang_scaler)

    return nlos_info_scaled, scaler_list
```

[12]:
```
def data_transform(dataset):
    """
    Main function to transform the raw train data into the proper shape for␣
↪training

    Parameters
    ----------
    dataset : from pickle file
        Train or test dataset

    Returns
    -------
    data_loader:  (n,124) array
        Scaled dataset
    scalar_list: list
        A list of scaler used for different link parameters
    """
    num_links = dataset['link_state'].shape[0]
    num_paths = 20
    nlos_info = np.zeros((num_links, 6*num_paths))
    data_loader = np.zeros((num_links, 6*num_paths+4))
    for ipath in range(num_paths):
```

```python
    nlos_info[:,ipath*6] = dataset['nlos_pl'][:,ipath]
    nlos_info[:,ipath*6+1] = dataset['nlos_dly'][:,ipath]
    nlos_info[:,ipath*6+2:ipath*6+6] = dataset['nlos_ang'][:,ipath,:]

  nlos_info, scaler_list = dataset_scaler(dataset['dvec'], nlos_info, num_paths)

  for ilk in range(num_links):
    dvec_this = dataset['dvec'][ilk,:]
    d_3D_this = np.linalg.norm(dvec_this)
    lkstate_this = dataset['link_state'][ilk]
    u = np.array([d_3D_this, 10*np.log10(d_3D_this), dvec_this[2],␣
↪lkstate_this])
    x = nlos_info[ilk,:]
    data_loader[ilk,:] = np.concatenate((u,x))
  return data_loader, scaler_list
```

[13]:
```python
# Transform the train and test datasets
# Order: d_3D, 10log10(d_3D), d_z, los/nlos, 6 parameters by 20 paths
train_samples,scaler_train = data_transform(train_data)
test_samples,scaler_test = data_transform(test_data)
```

[14]:
```python
# Hyperparameters for the link prediction network
input_size = 8 # tx_pos, rx_pos, d_3D and d_z
label_size = 3
BATCH_SIZE = 128
```

[15]:
```python
# Extract the data and label used for the link prediction network
num_samples_train = train_samples.shape[0]

lsp_train = np.concatenate((train_samples[:,[0,2]], train_data['tx_pos'],␣
↪train_data['rx_pos']), axis=1)
lsp_test = np.concatenate((test_samples[:,[0,2]], test_data['tx_pos'],␣
↪test_data['rx_pos']), axis=1)
all_samples = np.concatenate((lsp_train, lsp_test))

# all_samples = np.concatenate((train_samples[:,[0,2]], test_samples[:,[0,2]]))
# link_train = train_samples[:,[0,2]]
# link_test = test_samples[:,[0,2]]

link_scaler = MinMaxScaler(feature_range=(0,1))
all_samples_scaled = link_scaler.fit_transform(all_samples)

link_train = all_samples_scaled[0:num_samples_train, :]
link_test = all_samples_scaled[num_samples_train:, :]
label_train = train_samples[:,3]
label_test = test_samples[:,3]
num_labels = len(np.unique(label_train))
```

```python
# One-hot encoded labels
label_train = to_categorical(label_train)
label_test = to_categorical(label_test)
```

[16]:
```python
# Train and test the link state net
def make_state_model():
  """
  Creat the link prediction network

  Returns
  -------
  model : Link predictor
  """
  model = Sequential()
  model.add(Dense(20, input_dim=input_size))
  model.add(Activation('sigmoid'))
  model.add(Dense(40))
  model.add(Activation('sigmoid'))
  model.add(Dense(label_size))
  model.add(Activation('softmax'))
  # model.summary()

  return model
```

[17]:
```python
# Instantiate the link state prediction net
link_state_model = make_state_model()
# Compile it with cross entropy loss and RMSprop optimizer
link_state_model.compile(loss='categorical_crossentropy',
              optimizer=RMSprop(learning_rate=1e-3),
              metrics=['accuracy'])
# Train the network
link_state_model.fit(link_train, label_train, epochs=1000,␣
 ↪batch_size=BATCH_SIZE,
                     verbose=0)

# Calculate the train accuracy
_, acc_train = link_state_model.evaluate(link_train,
                        label_train,
                        batch_size=BATCH_SIZE,
                        verbose=0)

# Calculate the test accuracy
_, acc_test = link_state_model.evaluate(link_test,
                        label_test,
                        batch_size=BATCH_SIZE,
                        verbose=0)
```

```python
print(f"Train accuracy: {100.0 * acc_train:.1f} \n Test accuracy: {100.0 *␣
↪acc_test:.1f}")
```

```
Train accuracy: 88.2
 Test accuracy: 83.4
```

[18]:
```python
def link_state_predict(model, data):
  """
  Predict the link state for the input data

  Parameters
  ----------
  model : Model
      Trained link prediction network
  data : (n,2) array
      The distance information as input data

  Returns
  -------
  link_state_arr : (n,) array
      Array of predicted state per link
  """
  num_links = data.shape[0]
  link_state_arr = np.zeros(num_links)
  for i in range(data.shape[0]):
    p_pred = model.predict(data[i,:].reshape((1,-1)))
    link_state_arr[i] = np.random.choice(3,p=p_pred[0])

  return link_state_arr
```

[19]:
```python
# Creat tensorflow batched datasets
train_dataset = tf.data.Dataset.from_tensor_slices(train_samples)
test_dataset = tf.data.Dataset.from_tensor_slices(test_samples)

BUFFERSIZE = train_samples.shape[0]
BATCH_SIZE = 64

train_dataset = train_dataset.shuffle(BUFFERSIZE).batch(BATCH_SIZE)
test_dataset = test_dataset.batch(BUFFERSIZE)
```

[20]:
```python
def build_generator(inputs,
                    path_size,
                    labels,
                    activation='sigmoid'):
  """
  Build the generator model of ACGAN

  Parameters
```

```
    ----------
    inputs : (None,20)
        Noise vectors
    path_size : (None, 120)
        Output path information
    labels : (None, 2)
        One-hot vector of LOS/NLOS
    activation : string
        activation function at the output layer


    Returns
    -------
    generator: Model
        Generator model of ACGAN
    """

    # Pre-defined two hidden layers with 32 and 64 nodes
    hidden_layers = [32, 64]

    inputs_label = [inputs, labels]
    x = concatenate(inputs_label, axis=1)

    # For each set of hidden layer, it contains:
    # one dense layer, one batch norm layer, and one activation layer
    for layer in hidden_layers:
      x = Dense(layer)(x)
      x = BatchNormalization(momentum=0.8)(x)
      x = LeakyReLU(alpha=0.2)(x)

    # Output layer with specified activation function
    x = Dense(path_size)(x)
    if activation is not None:
      x = Activation(activation)(x)
    generator = Model(inputs_label, x, name='generator')

    return generator
```

[21]:
```
def build_discriminator(inputs,
                        num_labels,
                        activation='sigmoid'):
    """
    Build the discriminator model of ACGAN

    Parameters
    ----------
    inputs : (None,120)
```

```
        Path vectors
    num_labels: scalar
        The number of labels (2)
    activation : string
        activation function at the output layer


    Returns
    -------
    generator: Model
        Generator model of ACGAN
    """
    x = inputs
    hidden_layers = [64, 32]
    for layer in hidden_layers:
      x = Dense(layer)(x)
      x = BatchNormalization(momentum=0.8)(x)
      x = LeakyReLU(alpha=0.2)(x)

    outputs = Dense(1)(x)

    if activation is not None:
      outputs = Activation(activation)(outputs)

    if num_labels:
      y = Dense(hidden_layers[1])(x)
      y = Dense(num_labels)(y)
      y = Activation('softmax',name='label')(y)
      outputs = [outputs, y]

    return Model(inputs, outputs, name='discriminator')
```

[22]:
```
def train(models, data, params):
    """
    Train the ACGAN (discriminator and generator iteratively)
    The train procedure is written and modified based on an open-source
    implementation:
    https://github.com/PacktPublishing/Advanced-Deep-Learning-with-Keras/
    blob/master/chapter5-improved-gan/acgan-mnist-5.3.1.py

    Parameters
    ----------
    models : Tuple of models
        generator model, discriminator model, and adversarial model
    data : Tuple of arrays
        train data and labels
    params : Tuple of hyperparameters
```

```
        batch_size,
        latent_size,
        train_steps,
        num_labels,
        num_samples_generate,
        model_name

    Returns
    -------
        trained generator and discriminator models
    """
    generator, discriminator, adversarial = models
    x_train, y_train = data
    batch_size, latent_size, train_steps, num_labels, num_samples_generate, \
          model_name = params
    save_interval = 100

    # Create input noise vectors and labels
    noise_input = np.random.uniform(-1.0,
                                    1.0,
                                    size=[num_samples_generate, latent_size])
    noise_label = np.eye(num_labels)[np.arange(0,num_samples_generate) %␣
↪num_labels]
    train_size = x_train.shape[0]

    # Train iterations begin
    for i in range(train_steps):
      rand_indexes = np.random.randint(0,
                                       train_size,
                                       size=batch_size)
      real_channs = x_train[rand_indexes]
      real_labels = y_train[rand_indexes]

      noise = np.random.uniform(-1.0, 1.0,
                                size=[batch_size, latent_size])

      fake_labels = np.eye(num_labels)[np.random.choice(num_labels,batch_size)]

      # Use generator to produce fake channel samples based on the noise vector␣
↪and
      # fake labels
      fake_channs = generator.predict([noise, fake_labels])
      x = np.concatenate((real_channs, fake_channs))
      labels = np.concatenate((real_labels, fake_labels))

      y = np.ones([2*batch_size, 1])
      y[batch_size:,:] = 0
```

```
    # Train discriminator to decide the real and fake samples and output the
    # determined labels
    metrics = discriminator.train_on_batch(x, [y,labels])

    # Print discriminator loss, label loss, and label acc.
    fmt = "%d: [disc loss: %f, lblloss: %f, lblacc: %f]"
    log = fmt % (i, metrics[0], metrics[2], metrics[4])

    # Train the adversarial using another set of fake channel samples and␣
↪labels
    noise = np.random.uniform(-1.0, 1.0, size=[batch_size, latent_size])
    fake_labels = np.eye(num_labels)[np.random.choice(num_labels, batch_size)]
    y = np.ones([batch_size, 1])
    metrics = adversarial.train_on_batch([noise,fake_labels],[y,fake_labels])
    # Print adversarial loss, label loss, and label acc.
    fmt = "%s: [advr loss: %f, lblloss: %f, lblacc: %f]"
    log = fmt % (log, metrics[0], metrics[2], metrics[4])

    # Print the log every 100 epochs
    if (i+1) % save_interval == 0:
      print(f"It's time to check channels babe - Epoch {i+1}")
      print(log)
```

[23]:
```
# Prepare datasets for training ACGAN
# Since the outage locations do not have any paths, thus these
# locations will not be considered in the GAN training.
# The LOS and NLOS links are picked out to form new datasets

x_train = train_samples[:,4:]
y_train = train_samples[:,3]
all_index = np.arange(y_train.shape[0])
good_index = np.setdiff1d(all_index,np.array(outage_index))
x_train = x_train[good_index,:]
y_train = y_train[good_index]
# Convert labels from 1 and 2 to 1 and 0, respectively
# Such operation is for to_categorical function
y_train = -y_train+2
num_labels = len(np.unique(y_train))
y_train = to_categorical(y_train,num_classes=num_labels)
```

[24]:
```
model_name = 'acgan_channmod'

# Set hyperparameters
latent_size = 20
path_size = 120
```

```
batch_size = 64
train_steps = 500
num_samples_generate = 32
lr = 2e-4
decay = 1e-8
input_shape = (x_train.shape[1], )
label_shape = (num_labels,)

# Instantiate discriminator network
inputs = Input(shape=input_shape,
                name='discriminator_input')

discriminator = build_discriminator(inputs, num_labels=num_labels)
optimizer = Adam(lr=lr)
# optimizer = RMSprop(lr=lr, decay=decay)
loss = ['binary_crossentropy', 'categorical_crossentropy']
discriminator.compile(loss=loss,
                      optimizer=optimizer,
                      metrics=['accuracy'])
discriminator.summary()


# Instantiate generator network
input_shape = (latent_size, )
inputs = Input(shape=input_shape, name='z_input')
labels = Input(shape=label_shape, name='labels')
generator = build_generator(inputs, path_size, labels=labels)
generator.summary()


# Instantiate adversarial network
optimizer = Adam(lr=lr*0.5)

# optimizer = RMSprop(lr=lr*0.5, decay=decay*0.5)
discriminator.trainable = False
adversarial = Model([inputs, labels],
                    discriminator(generator([inputs,labels])),
                    name=model_name)
adversarial.compile(loss=loss,
                    optimizer=optimizer,
                    metrics=['accuracy'])
adversarial.summary()

models = (generator, discriminator, adversarial)
data = (x_train,y_train)
params = (batch_size, latent_size, train_steps, num_labels,\
          num_samples_generate, model_name)
```

```
train(models, data, params)
```

```
Model: "discriminator"
__________________________________________________________________________________
__________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================
==================
discriminator_input (InputLayer [(None, 120)]        0

__________________________________________________________________________________
__________________
dense_3 (Dense)                 (None, 64)           7744
discriminator_input[0][0]

__________________________________________________________________________________
__________________
batch_normalization (BatchNorma (None, 64)           256         dense_3[0][0]

__________________________________________________________________________________
__________________
leaky_re_lu (LeakyReLU)         (None, 64)           0
batch_normalization[0][0]

__________________________________________________________________________________
__________________
dense_4 (Dense)                 (None, 32)           2080
leaky_re_lu[0][0]

__________________________________________________________________________________
__________________
batch_normalization_1 (BatchNor (None, 32)           128         dense_4[0][0]

__________________________________________________________________________________
__________________
leaky_re_lu_1 (LeakyReLU)       (None, 32)           0
batch_normalization_1[0][0]

__________________________________________________________________________________
__________________
dense_6 (Dense)                 (None, 32)           1056
leaky_re_lu_1[0][0]

__________________________________________________________________________________
__________________
dense_5 (Dense)                 (None, 1)            33
leaky_re_lu_1[0][0]

__________________________________________________________________________________
__________________
dense_7 (Dense)                 (None, 2)            66          dense_6[0][0]

__________________________________________________________________________________
__________________
activation_3 (Activation)       (None, 1)            0           dense_5[0][0]

__________________________________________________________________________________
__________________
label (Activation)              (None, 2)            0           dense_7[0][0]
```

```
==================================================================================
==================
Total params: 11,363
Trainable params: 11,171
Non-trainable params: 192
__________________________________________________________________________________
__________________
Model: "generator"
__________________________________________________________________________________
__________________
Layer (type)                    Output Shape          Param #     Connected to
==================================================================================
==================
z_input (InputLayer)            [(None, 20)]          0
__________________________________________________________________________________
__________________
labels (InputLayer)             [(None, 2)]           0
__________________________________________________________________________________
__________________
concatenate (Concatenate)       (None, 22)            0           z_input[0][0]
                                                                  labels[0][0]
__________________________________________________________________________________
__________________
dense_8 (Dense)                 (None, 32)            736
concatenate[0][0]
__________________________________________________________________________________
__________________
batch_normalization_2 (BatchNor (None, 32)            128         dense_8[0][0]
__________________________________________________________________________________
__________________
leaky_re_lu_2 (LeakyReLU)       (None, 32)            0
batch_normalization_2[0][0]
__________________________________________________________________________________
__________________
dense_9 (Dense)                 (None, 64)            2112
leaky_re_lu_2[0][0]
__________________________________________________________________________________
__________________
batch_normalization_3 (BatchNor (None, 64)            256         dense_9[0][0]
__________________________________________________________________________________
__________________
leaky_re_lu_3 (LeakyReLU)       (None, 64)            0
batch_normalization_3[0][0]
__________________________________________________________________________________
__________________
dense_10 (Dense)                (None, 120)           7800
leaky_re_lu_3[0][0]
__________________________________________________________________________________
```

```
------------------
activation_4 (Activation)       (None, 120)          0           dense_10[0][0]
================================================================================
==================
Total params: 11,032
Trainable params: 10,840
Non-trainable params: 192
--------------------------------------------------------------------------------
------------------
Model: "acgan_channmod"
--------------------------------------------------------------------------------
------------------
Layer (type)                    Output Shape         Param #     Connected to
================================================================================
==================
z_input (InputLayer)            [(None, 20)]         0
--------------------------------------------------------------------------------
------------------
labels (InputLayer)             [(None, 2)]          0
--------------------------------------------------------------------------------
------------------
generator (Functional)          (None, 120)          11032       z_input[0][0]
                                                                 labels[0][0]
--------------------------------------------------------------------------------
------------------
discriminator (Functional)      [(None, 1), (None, 2 11363       generator[0][0]
================================================================================
==================
Total params: 22,395
Trainable params: 10,840
Non-trainable params: 11,555
--------------------------------------------------------------------------------
------------------
It's time to check channels babe - Epoch 100
99: [disc loss: 0.826155, lblloss: 0.511124, lblacc: 0.781250]: [advr loss:
1.955755, lblloss: 0.418675, lblacc: 0.875000]
It's time to check channels babe - Epoch 200
199: [disc loss: 0.600177, lblloss: 0.402565, lblacc: 0.812500]: [advr loss:
2.149458, lblloss: 0.189683, lblacc: 1.000000]
It's time to check channels babe - Epoch 300
299: [disc loss: 0.504735, lblloss: 0.300037, lblacc: 0.867188]: [advr loss:
2.175760, lblloss: 0.101489, lblacc: 0.984375]
It's time to check channels babe - Epoch 400
399: [disc loss: 0.510849, lblloss: 0.287743, lblacc: 0.867188]: [advr loss:
2.081630, lblloss: 0.073070, lblacc: 1.000000]
It's time to check channels babe - Epoch 500
499: [disc loss: 0.492680, lblloss: 0.259254, lblacc: 0.921875]: [advr loss:
1.743250, lblloss: 0.059800, lblacc: 1.000000]
```

[25]:
```python
def link_generator(generator, num_links, class_label=None):
    """
    Generate link information based on labels using the trained generator

    Parameters
    ----------
    generator : Model
        Trained generator network
    num_links : scalar (n)
        The number of links to generate
    class_labels : (n,) array
        The label - LOS or NLOS

    Returns
    -------
    output_channs: (n,120) array
        Generated channel samples
    """
    noise_input =np.random.uniform(-1.0, 1.0, size=[num_links, latent_size])
    if class_label is None:
      num_labels = 2
      noise_label = np.eye(num_labels)[np.random.choice(num_labels, num_links)]
    else:
      noise_label = -class_label+2
      noise_label = to_categorical(noise_label)

    output_channs = generator.predict([noise_input, noise_label])

    return output_channs
```

[26]:
```python
# Use link state predictor to predict the link state of test data
test_link_state = link_state_predict(link_state_model,link_test)

# Remove the predicted outage locations
test_good_index = np.where(test_link_state != 0)
test_good_states = test_link_state[test_good_index]
```

[27]:
```python
# Generate channel samples based on the predicted states
output_channs = link_generator(generator, test_good_states.shape[0],␣
 ↪class_label=test_good_states)
```

[28]:
```python
# Inverse tranform the generated channel information to their original scales
pll = scaler_train[0].inverse_transform(output_channs[:,np.
 ↪array(range(num_paths))*6])
dlyy = scaler_train[1].inverse_transform(output_channs[:,np.
 ↪array(range(num_paths))*6+1])
```

```
ang_index = np.arange(4).reshape((1,-1)) + np.arange(20).reshape((-1,1))*6 + 2
ang_index = ang_index.reshape((1,-1))[0]

angg = scaler_train[2].inverse_transform(output_channs[:,ang_index])

# Save generated samples into result_channs
result_channs = np.zeros_like(output_channs)
result_channs[:,np.array(range(num_paths))*6] = pll
result_channs[:,np.array(range(num_paths))*6+1] = dlyy
result_channs[:,ang_index] = angg
```

[29]:
```
# Prepare to save the generated channels with corresponding distance information
dist_info = test_samples[test_good_index,0:3][0]
gen_channs = np.concatenate((dist_info, test_good_states.reshape((-1,1)),␣
↪result_channs), axis=1)
```

[30]:
```
# Save the generated and ground truth channel samples
save_fd = os.path.join(main_path, "results", "generated_paths.csv")
pd.DataFrame(gen_channs).to_csv(save_fd)
save_fd2 = os.path.join(main_path, "results", "meas_paths.csv")
pd.DataFrame(test_samples[test_good_index,:][0]).to_csv(save_fd2)
```

[31]:
```
# Import several helper functions for plotting functions
# from mmwchanmod.common.spherical import spherical_add_sub, cart_to_sph
from mmwchanmod.common.constants import PhyConst, AngleFormat
from mmwchanmod.common.constants import LinkState

import math
```

[32]:
```
class resultsPlotGAN(object):
    def __init__(self,training_data,generated_data):
        """
        GAN results evaluation class

        Parameters
        ----------
        training_data : pandas dataframe
            data used to train the GAN
        generated_data : array, float
            output of the GAN ("fake" data)

        """
        self.training_data = training_data
        self.generated_data = generated_data

    def eval_plos(self):
        """
```

```
        Plots the probability of LOS as a function of distance

        """
        # Get the test data vector
        dvec = self.training_data['dvec']
        dx = np.sqrt(dvec[:,0]**2 + dvec[:,1]**2)
        dz = dvec[:,2]

        # Get the link state data
        link_state = self.training_data['link_state']
        los = (link_state == LinkState.los_link)

        # Get the link state for generated paths
        d3D = self.generated_data[:,0]
        dz_gen = self.generated_data[:,2]
        dx_gen = np.sqrt(d3D**2 - dz_gen**2)

        link_state_gen = self.generated_data[:,3]

        los_gen = (link_state_gen == LinkState.los_link)

        # Extract the correct points
        I0 = np.where(los)[0]
        I1 = np.where(los_gen)


        # Set plotting limits
        xlim = np.array([np.min(dx), np.max(dx)])
        zlim = np.array([np.min(dz), np.max(dz)])

        # Set plotting limits
        xlim_gen = np.array([np.min(dx_gen), np.max(dx_gen)])
        zlim_gen = np.array([np.min(dz_gen), np.max(dz_gen)])

        # Compute the empirical probability for dataset
        H0, xedges, zedges = np.
↪histogram2d(dx[I0],dz[I0],bins=[20,2],range=[xlim,zlim])
        Htot, xedges, zedges = np.
↪histogram2d(dx,dz,bins=[20,2],range=[xlim,zlim])
        prob_ts = H0 / np.maximum(Htot,1)
        prob_ts = np.flipud(prob_ts.T)

        # Compute the empirical probability for generated data
        H1, xedges, zedges = np.
↪histogram2d(dx_gen[I1],dz_gen[I1],bins=[20,2],range=[xlim_gen,zlim_gen])
        Htot, xedges, zedges = np.
↪histogram2d(dx_gen,dz_gen,bins=[20,2],range=[xlim_gen,zlim_gen])
```

```
        prob_gen = H1 / np.maximum(Htot,1)
        prob_gen = np.flipud(prob_gen.T)

        # Plot the results
        plt.subplot(1,2,1)
        plt.imshow(prob_ts,aspect='auto',\
               extent=[np.min(xedges),np.max(xedges),np.min(zedges),np.
↪max(zedges)],\
               vmin=0, vmax=1)
        plt.title('Data')
        plt.ylabel('Elevation (m)')

        plt.xlabel('Horiz (m)')

        # Plot the results
        plt.subplot(1,2,2)
        plt.imshow(prob_gen,aspect='auto',\
               extent=[np.min(xedges),np.max(xedges),np.min(zedges),np.
↪max(zedges)],\
               vmin=0, vmax=1)
        plt.title('Generated')

        plt.xlabel('Horiz (m)')

        plt.tight_layout()
        plt.subplots_adjust(bottom=0.1, right=0.87, top=0.9)
        cax = plt.axes([0.92, 0.1, 0.05, 0.8])
        plt.colorbar(cax=cax)


    def eval_path_loss(self, npath_gen):
        """
        Plots the CDF of the path loss of both data and generated samples

        """

        # Flatten the array of ray traced path losses
        path_loss_dat = np.ndarray.flatten(self.training_data['nlos_pl'][:,:24])

        # Get array of the generated path losses
        path_loss_gen = []
        for n in range(npath_gen):
            path_loss_gen = np.append(path_loss_gen,self.generated_data[:
↪,4+n*6])

        # Plot the CDF
        p1 = len(path_loss_dat)
```

```
        p2 = len(path_loss_gen)

        plt.plot(np.sort(path_loss_dat),np.arange(p1)/p1,\
                 label = "Data Samples")
        plt.plot(np.sort(path_loss_gen),np.arange(p2)/p2,\
                 label = "Generated Samples")

        plt.xlabel('Path Loss [dB]')
        plt.ylabel('CDF')

        plt.legend()
        plt.grid()
        plt.show()


    def eval_angular_spread(self,npath_gen):
        """
        Computes and plots the angular spread of each AoD, ZoD, AoA, and ZoA
        for both data and generated samples.
        Computation of angular spread taken from 3GPP 38.901 Annex A.

        """
        # Get the sample (true) angular data
        nDatSamp = len(self.training_data['nlos_ang'])
        nPathsSamp = 24

        ang_dat = self.training_data['nlos_ang'][:,:nPathsSamp,:]

        # Get the generated (fake) angular data
        nGenSamp = len(self.generated_data)
        ang_gen = np.zeros([nGenSamp,npath_gen,4])
        for n in range(npath_gen):
            ang_gen[:,n,:] = self.generated_data[:,6+n*6:10+n*6]

        # Get the sample path loss data
        path_loss_dat = self.training_data['nlos_pl'][:,:nPathsSamp]

        # Get the generated path loss data
        path_loss_gen = np.zeros([nGenSamp,npath_gen])
        for n in range(npath_gen):
            path_loss_gen[:,n] = self.generated_data[:,4+n*6]

        # Convert gains to linear scale
        path_loss_dat = 10**(-0.05*path_loss_dat)
        path_loss_gen = 10**(-0.05*path_loss_gen)

        # Separate data angles, convert to radians
```

```python
    aod_dat = ang_dat[:,:,0]*math.pi/180
    zod_dat = ang_dat[:,:,1]*math.pi/180
    aoa_dat = ang_dat[:,:,2]*math.pi/180
    zoa_dat = ang_dat[:,:,3]*math.pi/180

    # Compute angular spreads of the data angles
    spread_aod_dat = np.zeros(nDatSamp)
    spread_zod_dat = np.zeros(nDatSamp)
    spread_aoa_dat = np.zeros(nDatSamp)
    spread_zoa_dat = np.zeros(nDatSamp)
    for n in range(nDatSamp):
        spread_aod_dat[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
                            np.exp(1j*aod_dat[n,:]),path_loss_dat[n,:]))\
                                    /np.sum(path_loss_dat[n,:]))))

        spread_zod_dat[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
                            np.exp(1j*zod_dat[n,:]),path_loss_dat[n,:]))\
                                    /np.sum(path_loss_dat[n,:]))))
        spread_aoa_dat[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
                            np.exp(1j*aoa_dat[n,:]),path_loss_dat[n,:]))\
                                    /np.sum(path_loss_dat[n,:]))))

        spread_zoa_dat[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
                            np.exp(1j*zoa_dat[n,:]),path_loss_dat[n,:]))\
                                    /np.sum(path_loss_dat[n,:]))))

    # Separate generated angles, convert to radians
    aod_gen = ang_gen[:,:,0]*math.pi/180
    zod_gen = ang_gen[:,:,1]*math.pi/180
    aoa_gen = ang_gen[:,:,2]*math.pi/180
    zoa_gen = ang_gen[:,:,3]*math.pi/180

    # Compute angular spreads of the generated angles
    spread_aod_gen = np.zeros(nGenSamp)
    spread_zod_gen = np.zeros(nGenSamp)
    spread_aoa_gen = np.zeros(nGenSamp)
    spread_zoa_gen = np.zeros(nGenSamp)
    for n in range(nGenSamp):
        spread_aod_gen[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
                            np.exp(1j*aod_gen[n,:]),path_loss_gen[n,:]))\
                                    /np.sum(path_loss_gen[n,:]))))

        spread_zod_gen[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
                            np.exp(1j*zod_gen[n,:]),path_loss_gen[n,:]))\
                                    /np.sum(path_loss_gen[n,:]))))

        spread_aoa_gen[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
```

```
                        np.exp(1j*aoa_gen[n,:]),path_loss_gen[n,:]))\
                                /np.sum(path_loss_gen[n,:]))))

    spread_zoa_gen[n] = np.sqrt(-2*np.log(np.abs(np.sum(np.multiply(\
                        np.exp(1j*zoa_gen[n,:]),path_loss_gen[n,:]))\
                                /np.sum(path_loss_gen[n,:]))))


# Plot CDFs of the angular spreads
fig, axs = plt.subplots(2, 2, constrained_layout=True)

# Azimuth of Departure
p1 = len(spread_aod_dat)
p2 = len(spread_aod_gen)

axs[0,0].plot(np.sort(spread_aod_dat),np.arange(p1)/p1,\
         label = "Dat")
axs[0,0].plot(np.sort(spread_aod_gen),np.arange(p2)/p2,\
         label = "Gen")

axs[0,0].set_xlabel('Angular Spread $\phi_{tx}$')
axs[0,0].set_ylabel('CDF')

axs[0,0].legend()
axs[0,0].grid()

# Zenith of Departure
p1 = len(spread_zod_dat)
p2 = len(spread_zod_gen)

axs[0,1].plot(np.sort(spread_zod_dat),np.arange(p1)/p1,\
         label = "Dat")
axs[0,1].plot(np.sort(spread_zod_gen),np.arange(p2)/p2,\
         label = "Gen")

axs[0,1].set_xlabel('Angular Spread $\\theta_{tx}$')
axs[0,0].set_ylabel('CDF')

axs[0,1].legend()
axs[0,1].grid()

# Azimuth of Arrival
p1 = len(spread_aoa_dat)
p2 = len(spread_aoa_gen)

axs[1,0].plot(np.sort(spread_aoa_dat),np.arange(p1)/p1,\
         label = "Dat")
```

```
    axs[1,0].plot(np.sort(spread_aoa_gen),np.arange(p2)/p2,\
             label = "Gen")

    axs[1,0].set_xlabel('Angular Spread $\phi_{rx}$')
    axs[1,0].set_ylabel('CDF')

    axs[1,0].legend()
    axs[1,0].grid()

    # Zenith of Arrival
    p1 = len(spread_zoa_dat)
    p2 = len(spread_zoa_gen)

    axs[1,1].plot(np.sort(spread_zoa_dat),np.arange(p1)/p1,\
             label = "Dat")
    axs[1,1].plot(np.sort(spread_zoa_gen),np.arange(p2)/p2,\
             label = "Gen")

    axs[1,1].set_xlabel('Angular Spread $\\theta_{rx}$')
    axs[1,1].set_ylabel('CDF')

    axs[1,1].legend()
    axs[1,1].grid()

    plt.show()


def eval_rms_delay(self,npath_gen):
    """
    Compares the RMS delay CDF of the true data to generated samples

    Parameters
    ----------
    npath_gen : int
        Number of generated paths to use

    Returns
    -------
    None.

    """
    nDatSamp = len(self.training_data['nlos_dly'])
    nPathsSamp = 24

    # Get the data sample (true) abosolute propagation delay data
    dly_dat = self.training_data['nlos_dly'][:,:nPathsSamp]
```

```
        # Get the generated (fake) abosolute propagation delay data
        nGenSamp = len(self.generated_data)
        dly_gen = np.zeros([nGenSamp,npath_gen])
        for n in range(npath_gen):
            dly_gen[:,n] = self.generated_data[:,5+n*6]

        # Get the sample path loss data
        path_loss_dat = self.training_data['nlos_pl'][:,:nPathsSamp]

        # Get the generated path loss data
        path_loss_gen = np.zeros([nGenSamp,npath_gen])
        for n in range(npath_gen):
            path_loss_gen[:,n] = self.generated_data[:,4+n*6]

        # Convert gains to linear scale
        path_loss_dat = 10**(-0.05*path_loss_dat)
        path_loss_gen = 10**(-0.05*path_loss_gen)

        # Compute mean delay for each link in both true and fake samples
        mean_dly_dat = np.sum(np.multiply(dly_dat,path_loss_dat),axis=1)\
                        /np.sum(path_loss_dat,axis=1)
        mean_dly_gen = np.sum(np.multiply(dly_gen,path_loss_gen),axis=1)\
                        /np.sum(path_loss_gen,axis=1)

        # Compute root mean square delay for data samples
        rms_dly_dat = np.zeros([nDatSamp])
        for n in range(nDatSamp):
            rms_dly_dat[n] = np.sqrt(np.sum(np.multiply(path_loss_dat[n,:],\
                             np.square(dly_dat[n,:]-mean_dly_dat[n])))\
                                        /np.sum(path_loss_dat[n,:]))

        # Compute root mean square delay for generated samples
        rms_dly_gen = np.zeros([nGenSamp])
        for n in range(nGenSamp):
            rms_dly_gen[n] = np.sqrt(np.sum(np.multiply(path_loss_gen[n,:],\
                             np.square(dly_gen[n,:]-mean_dly_gen[n])))\
                                        /np.sum(path_loss_gen[n,:]))

        # Plot the CDF
        plt.figure()

        p1 = len(rms_dly_dat)
        p2 = len(rms_dly_gen)

        plt.plot(np.sort(rms_dly_dat*1e6),np.arange(p1)/p1,\
                 label = "Data Samples")
        plt.plot(np.sort(rms_dly_gen*1e6),np.arange(p2)/p2,\
```

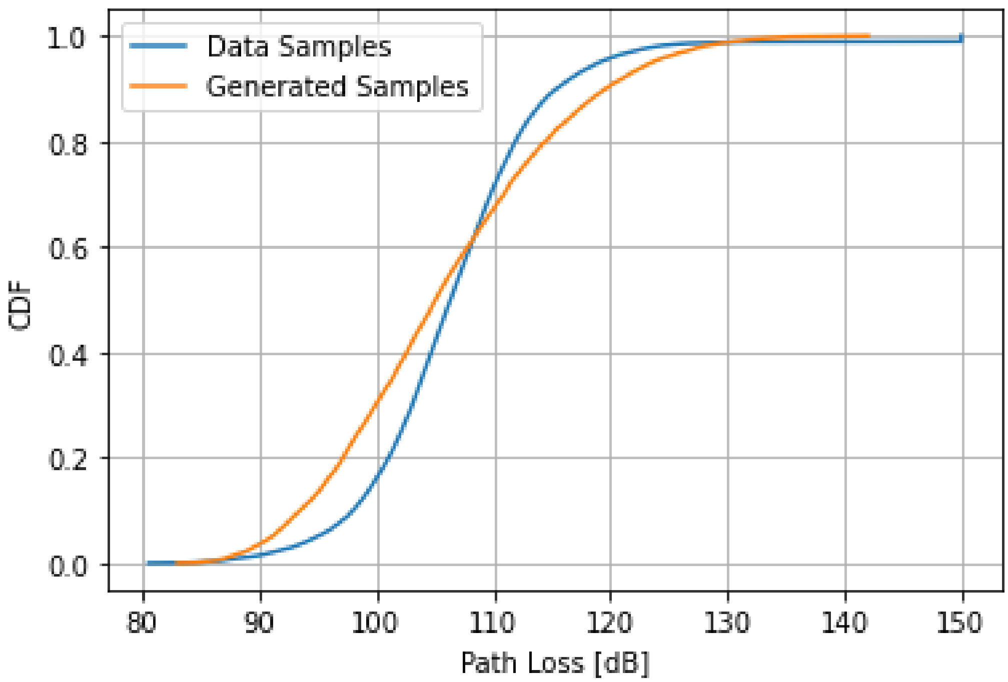
```
                 label = "Generated Samples")

        plt.xlabel('RMS Delay [$\mu$s]')
        plt.ylabel('CDF')

        plt.legend()
        plt.grid()
        plt.show()
```

[33]:

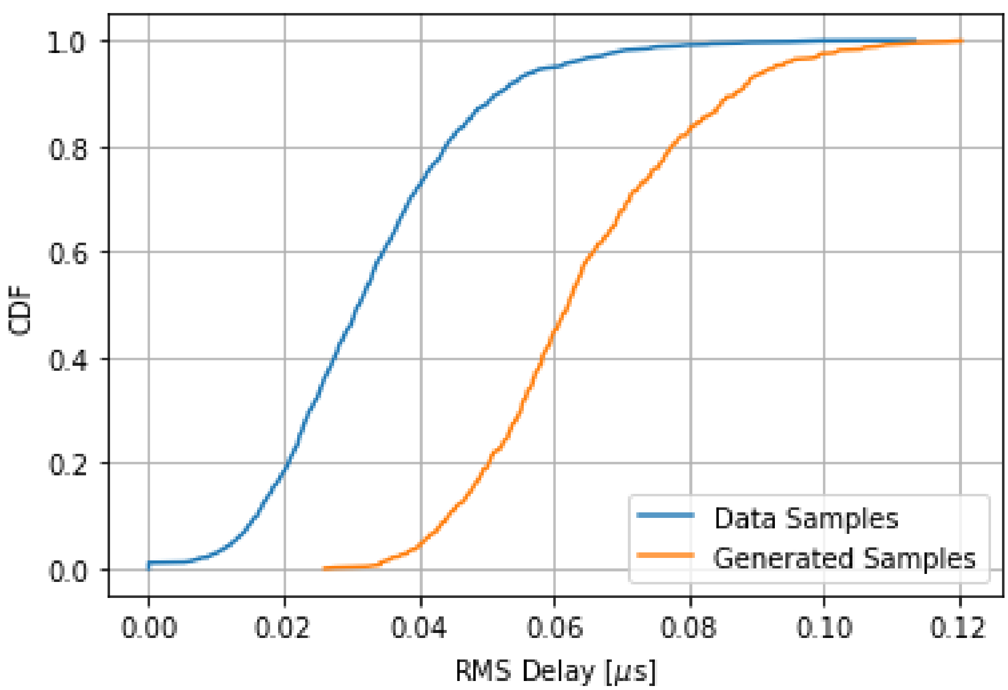
```
# Read the saved generated and ground truth data for evaluation
gan_out_fn = save_fd
tr_data_fn = os.path.join(main_path, "factory_warehouse.p")

nPath_gen = 20

# Get generated output csv from GAN
gen_samp_df = pd.read_csv(gan_out_fn)

gen_samp = np.array(gen_samp_df)[:,1:]

# Get training data file
dat_samp = pickle.load(open(tr_data_fn,"rb"))[1]

# Create plotter object
results = resultsPlotGAN(dat_samp, gen_samp)
```

[34]:

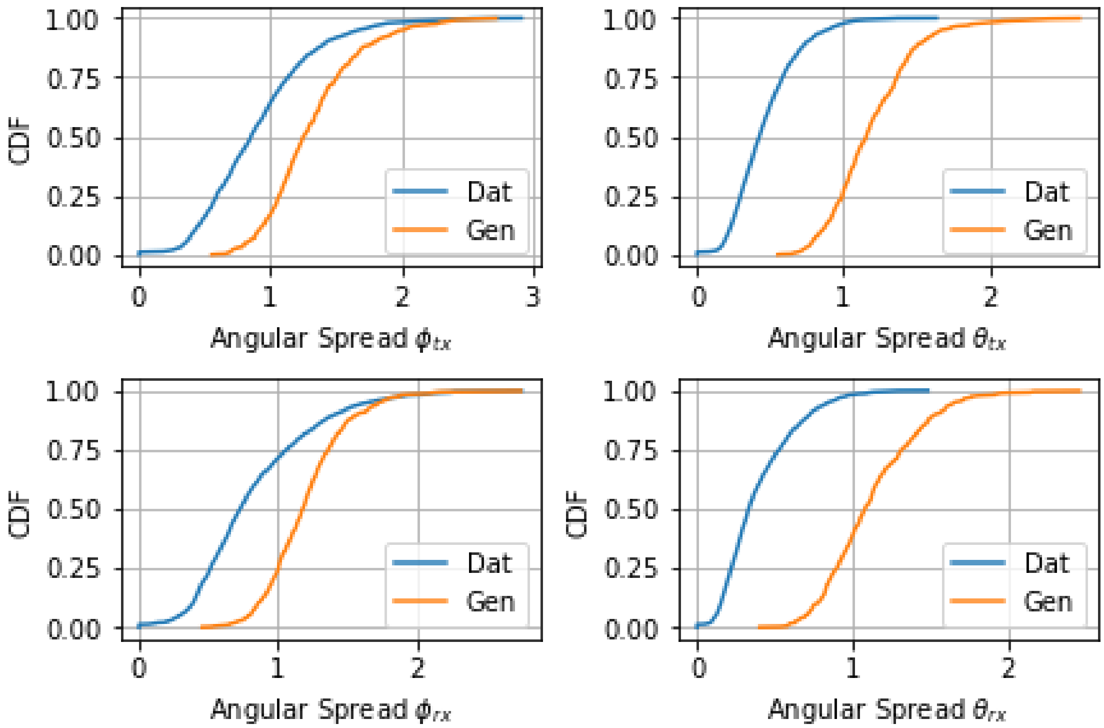
```
# Evaluate path loss
results.eval_path_loss(nPath_gen)
```



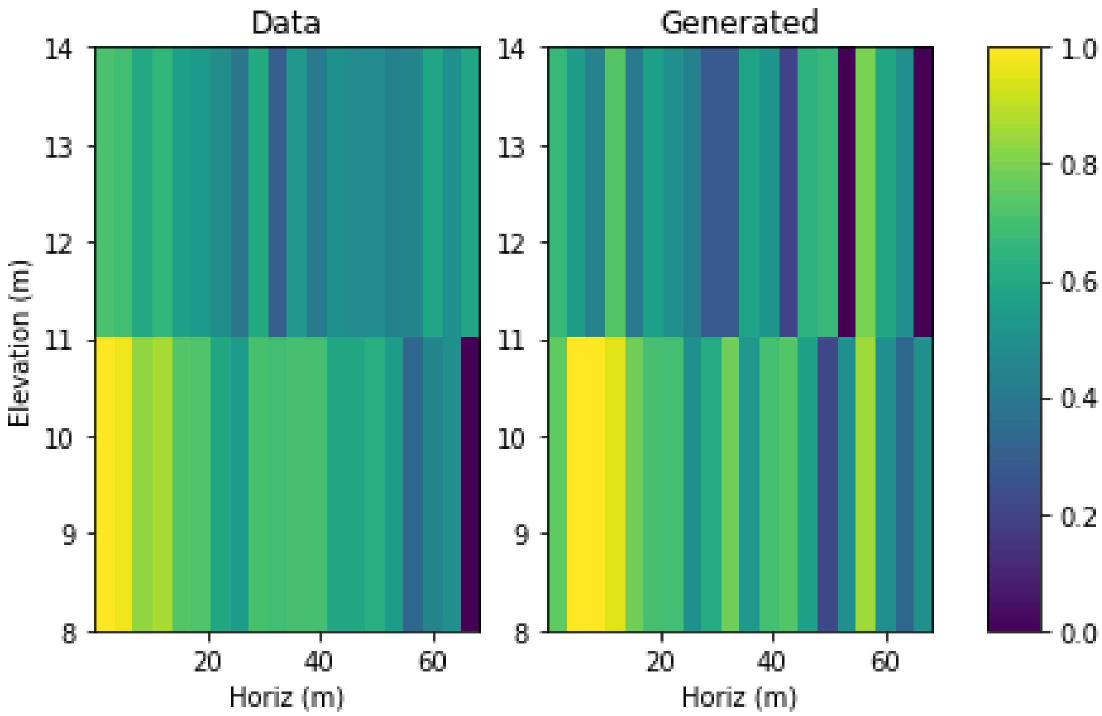
[35]:
```
# Evaluate RMS delay spread
results.eval_rms_delay(nPath_gen)
```



[36]:
```
# Evaluate angular spread
results.eval_angular_spread(nPath_gen)
```



[37]:
```
# Evaluate LOS probability
results.eval_plos()
```

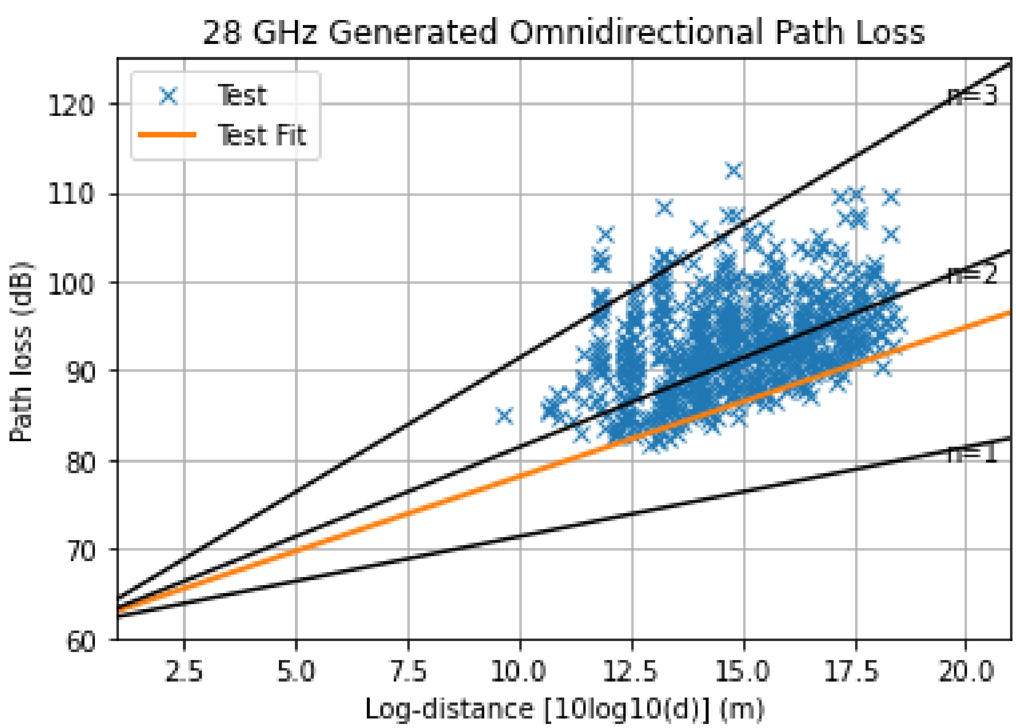



```
[57]: # Prepare the generated data for path loss scatter plot against distance
nlos_pls = gen_samp[:,np.array(range(nPath_gen))*6+4]
nlos_prs_lin = np.sum(10**((0-nlos_pls)/10),axis=1)
nlos_prs = 10*np.log10(nlos_prs_lin)
nlos_pls = -nlos_prs
nlos_d = gen_samp[:,0]
```

```
[57]: array([89.12863354, 86.90123968, 86.17534579, 82.92978862, 82.63297226,
       87.80518077, 87.8586978 , 81.70730883, 87.07837575, 88.20937641])
```

```
[63]: # Compute the PLE and SF for generated data
ple_nlos, sf_nlos_std = compute_ple(nlos_d,
                                    nlos_pls, fc, d0)

# Scatter plot
plt.plot(10*np.
 ↪log10(train_data['dist'][nlos_index]),train_data['pl_omni'][nlos_index],'x',c='C0')
plt.xlim([1,21])
plt.ylim([60,125])

# Plot the fit line
plt.plot(np.linspace(0,21,num=100),fspl0+ple_nlos*np.linspace(0,21,num=100),
         c='C1',lw=2)
```

```
plt.legend(['Test','Test Fit'])

# Plot the reference lines
plt.plot(np.linspace(0,21,num=100),fspl0+2*np.linspace(0,21,num=100),'k')
plt.plot(np.linspace(0,21,num=100),fspl0+1*np.linspace(0,21,num=100),'k')
plt.plot(np.linspace(0,21,num=100),fspl0+3*np.linspace(0,21,num=100),'k')
plt.annotate('n=1',(19.5,80))
plt.annotate('n=2',(19.5,100))
plt.annotate('n=3',(19.5,120))
plt.title('28 GHz Generated Omnidirectional Path Loss')
plt.xlabel('Log-distance [10log10(d)] (m)')
plt.ylabel('Path loss (dB)')
plt.grid(True)
plt.show()

print(f'NLOS locations - PLE:{ple_nlos:.2f}, SF:{sf_nlos_std:.2f}')
```




```
NLOS locations - PLE:1.67, SF:4.50
```