6 - NFN

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1 Implementação de um Sistema de Inferência NFN

Nesta etapa será implementada o sistema mebuloso adaptativo NFN (NEO-FUZZY-NEURON)

[1]:
```
from matplotlib import pyplot as plt
import numpy as np
from math import *
from sklearn.metrics import mean_squared_error
import skfuzzy as fuzz
from skfuzzy import control as ctrl
from sklearn import datasets
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import random
import collections
import pandas as pd
from sklearn.utils import shuffle
from sklearn.base import BaseEstimator, ClassifierMixin
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
```

[27]:
```
class NFN(BaseEstimator, ClassifierMixin):
    def __init__(self, n_inputs, n_rules, lr = 0.8, n_epochs=100):
        self.n_rules = n_rules
        self.n_inputs = n_inputs
        self.w = np.zeros([self.n_inputs, self.n_rules])
        self.P = np.random.randn(self.n_inputs, self.n_rules)
        self.q = np.random.randn(self.n_rules)
        self.lr = lr
        self.n_epochs = n_epochs

    # X - dados de entrada
    # y - saídas esperadas
    # n_epochs - maximo de épocas
```

```python
    # lr - learning rate
    def fit(self, X, y_real):
        self.mse = []
        # Estrutura de repetição para número de épocas

        self.delta = np.zeros(X.shape[1])
        self.X_min = np.zeros(X.shape[1])
        self.X_max = np.zeros(X.shape[1])
        for j in range(X.shape[1]):
            self.X_min[j] = np.min(X[:, j])
            self.X_max[j] = np.max(X[:, j])
            self.delta[j] = (self.X_max[j] - self.X_min[j]) / (self.n_rules-1)

        for epoch in range(self.n_epochs):
            #X, y_real = shuffle(X, y_real)
            # Estrutura de repetição para o números de pontos
            for k in range(X.shape[0]):
                # Apresentação dos dados a rede e cálculo da saída para os␣
↪parâmetros atuais
                y_hat = 0
                sum_alpha = 0
                kk = np.zeros((X.shape[1], 2))
                mk = np.zeros((X.shape[1], 2))
                # Estrutura de repetição para o número de regras
                for i in range(X.shape[1]):
                    x_min = self.X_min[i]
                    x_max = self.X_max[i]
                    delta = self.delta[i]

                    # k1 - primeira função de pertinência ativa
                    # mk1 - valor correspondente a função ativa
                    if X[k, i] <= x_min:
                        k1 = 0
                        mk1 = 1
                    elif X[k, i] >= x_max:
                        k1 = self.n_rules - 1 - 1  #because python first index␣
↪is 0

                        mk1 = 0
                    else:
                        k1 = int((X[k, i] - x_min)/delta) - 1 - 1
                        mk1 = int(-X[k, i] + x_min + k1*delta)/delta

                    mk2 = 1 - mk1
                    k2 = k1 + 1
                    sum_alpha = sum_alpha + (mk1**2 + mk2**2)
                    #print(k2)
                    yi = mk1 * self.w[i, k1] + mk2 * self.w[i, k2]
```

```
                    y_hat = y_hat + yi

                    kk[i, :] = [int(k1), int(k2)]
                    mk[i, :] = [mk1, mk2]

                alpha = self.lr * (1 / sum_alpha)
                error = (y_hat -  y_real[k]);

                for i in range(X.shape[1]):
                    #print(kk[i, 0])
                    self.w[i, int(kk[i, 0])] = self.w[i, int(kk[i, 0])] - alpha * error * mk[i, 0]
                    self.w[i, int(kk[i, 1])] = self.w[i, int(kk[i, 1])] - alpha * error * mk[i, 1];
            # Calculo do erro quadrático
            self.mse.append(mean_squared_error(y_real, self.predict(X)))

    def predict(self, X):
        y_hat = []
        for k in range(X.shape[0]):
            yhat = 0
            for i in range(X.shape[1]):
                x_min = self.X_min[i]
                x_max = self.X_max[i]
                delta = self.delta[i]
                # k1 - primeira função de pertinência ativa
                # mk1 - valor correspondente a função ativa
                if X[k, i] <= x_min:
                    k1 = 0
                    mk1 = 1
                elif X[k, i] >= x_max:
                    k1 = self.n_rules - 1 - 1  #because python first index is 0
                    mk1 = 0
                else:
                    k1 = int((X[k, i] - x_min)/delta) - 1 - 1
                    mk1 = int(-X[k, i] + x_min + k1*delta)/delta
                mk2 = 1 - mk1
                k2 = k1 + 1
                yi = mk1 * self.w[i, k1] + mk2 * self.w[i, k2]
                yhat = yhat + yi
            y_hat.append(yhat)
        #print(y_hat)
        return np.array(y_hat)
```

2 Problema 1 - Modelagem de sistema estático monovariável

Aproximar a função $y = x^2$.

2.1 Geração dos Dados

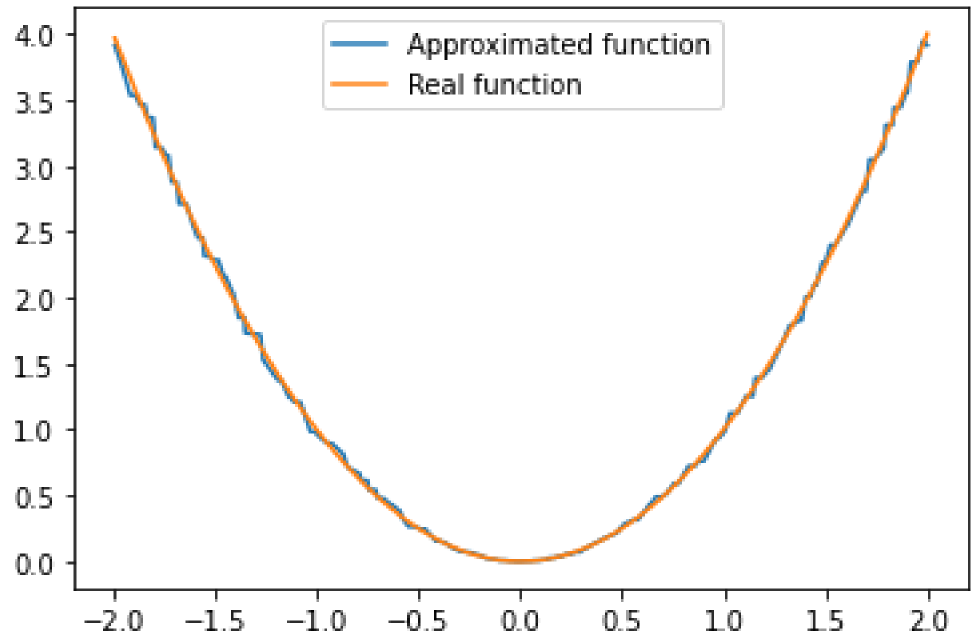
[3]:
```
# Generating Data
N = 1000
X = np.linspace(-2, 2, N).reshape(-1, 1)
y = X ** 2
```

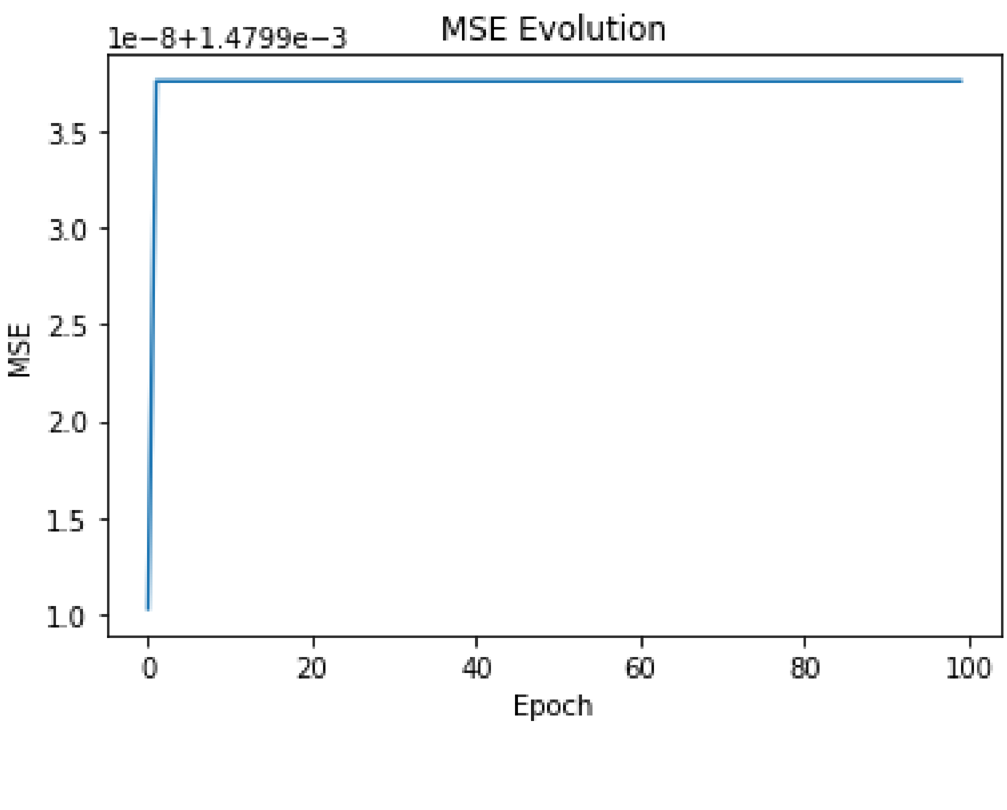
2.2 Aplicação do Anfis desenvolvido

[7]:
```
# Train and Test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Anfis
model =NFN(n_rules = 100, n_inputs = 1, n_epochs=100, lr=0.9)
#model.initialize_params(X = X_train)
model.fit(X_train, y_train)

# Eval fis
yhat = model.predict(X_test).reshape(-1, 1)
mse = mean_squared_error(y_test, yhat)
print(f'mse: {mse}')

# Plot functions (real and approximated)
xx, yy = zip(*sorted(zip(X_test, yhat)))
plt.plot(xx, yy)
xx, yy = zip(*sorted(zip(X_test, y_test)))
plt.plot(xx, yy)
plt.legend(["Approximated function", "Real function"])

# Plot MSE Evolution
plt.figure()
plt.plot(model.mse)
plt.title("MSE Evolution")
plt.xlabel("Epoch")
plt.ylabel("MSE")
```

```
mse: 0.0017402017951344472
```

[7]:
```
Text(0, 0.5, 'MSE')
```


Approximated function
Real function
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


MSE Evolution
1e−8+1.4799e−3
MSE
3.5
3.0
2.5
2.0
1.5
1.0
0
20
40
60
80
100
Epoch

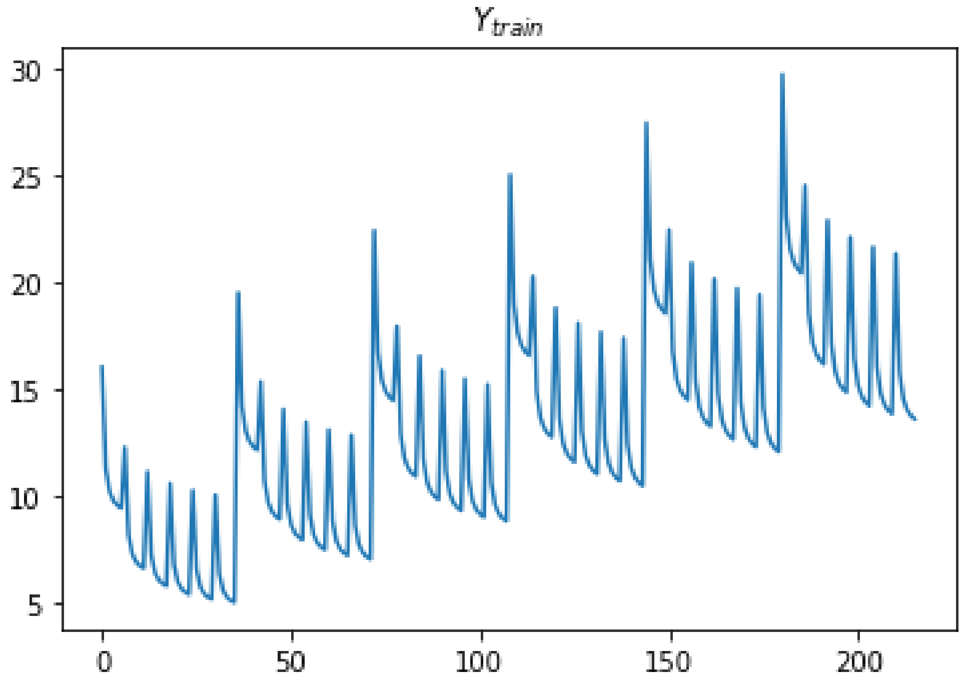
3 Problema 2 - Modelagem de sistema estático multivariável

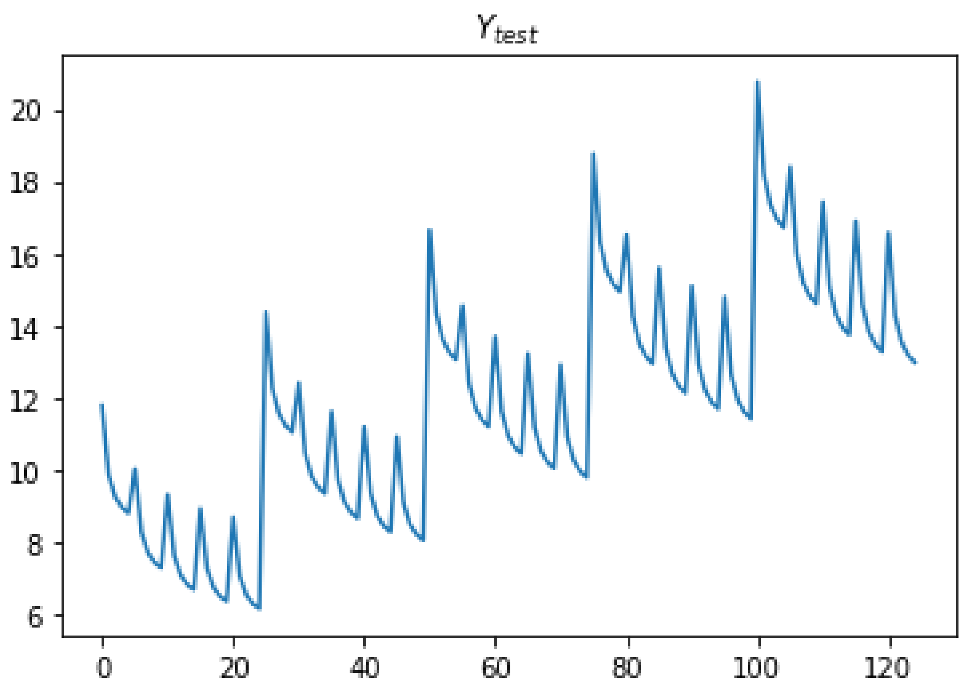
Modelar uma função não linear de 3 entradas:
$output = (1 + x^{0.5} + y^{-1} + z^{-1.5})^2$

3.1 Geração dos dados:

[28]:
```
i = 0
X_train = []
y_train = []
X_test = []
y_test = []
for x1 in range(1, 7):
    for x2 in range(1, 7):
        for x3 in range(1, 7):
            X_train.append([x1, x2, x3])
            y_train.append((1 + x1**0.5 + x2**(-1) + x3**(-1.5))**2)
for x1 in range(1, 6):
    for x2 in range(1, 6):
        for x3 in range(1, 6):
            X_test.append([x1+0.5, x2+0.5, x3+0.5])
            y_test.append((1 + (x1+0.5)**0.5 + (x2+0.5)**(-1) + (x3+0.5)**(-1.
 ↪5))**2)
plt.plot(y_train)
plt.title("$Y_{train}$")
plt.figure()
plt.plot(y_test)
plt.title("$Y_{test}$")
```

[28]:
```
Text(0.5, 1.0, '$Y_{test}$')
```


Y_{train}
30
25
20
15
10
5
0
50
100
150
200

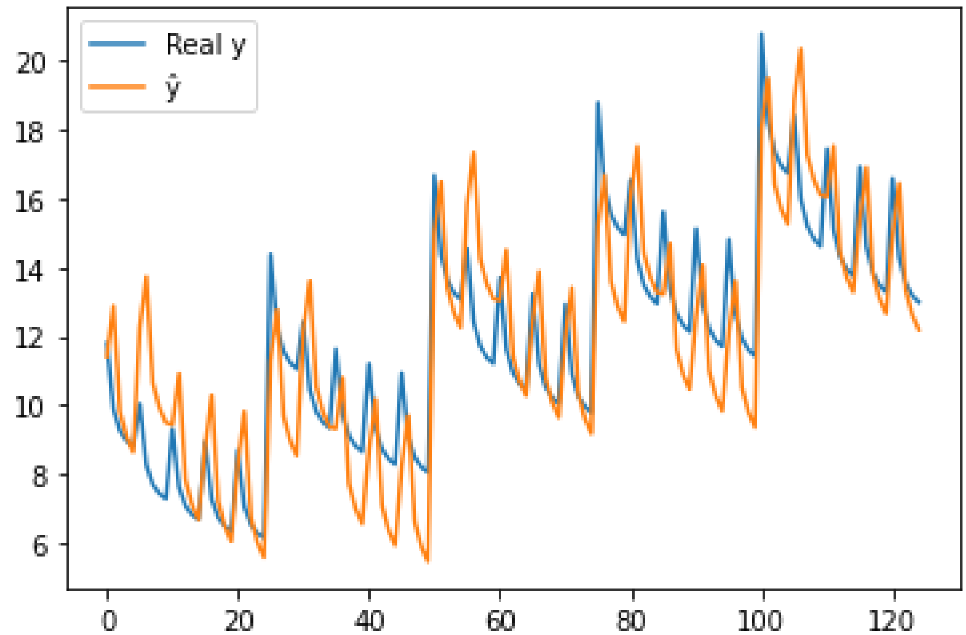

Y_{test}
20
18
16
14
12
10
8
6
0
20
40
60
80
100
120

3.2 Aplicação do Anfis desenvolvido

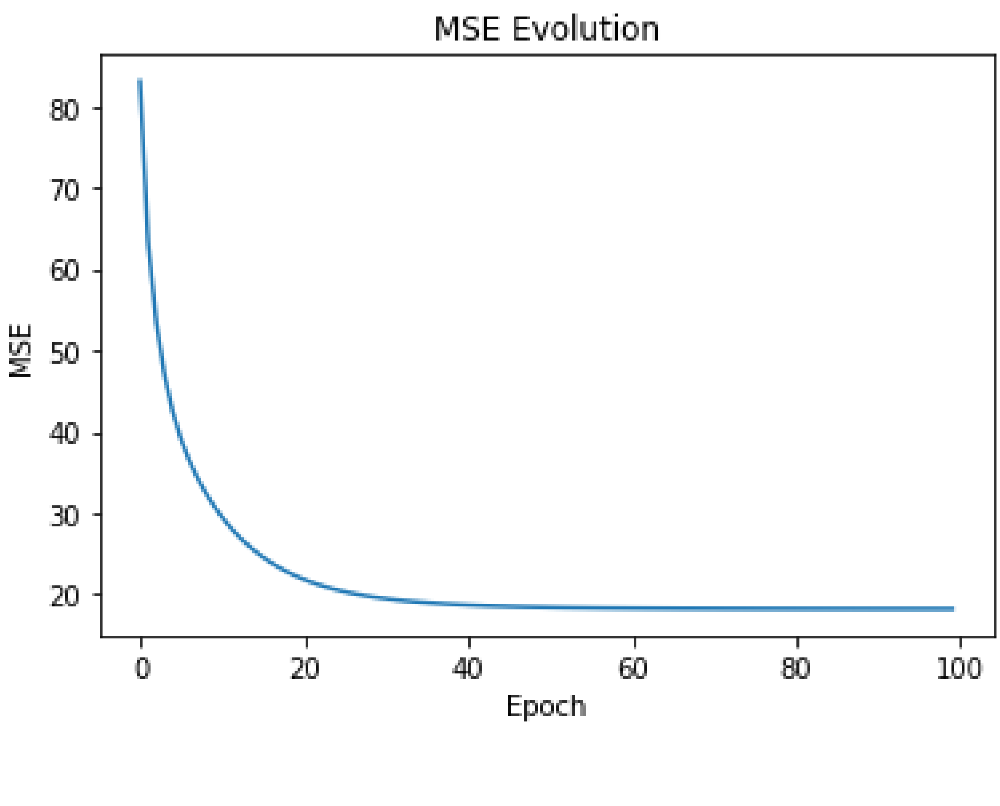
[49]:
```
X_train = np.array(X_train)
y_train = np.array(y_train)
X_test = np.array(X_test)
y_test = np.array(y_test)

model = NFN(n_inputs = X_train.shape[1], n_rules = 5, n_epochs=100, lr=0.04)
model.fit(X_train, y_train)

# Eval fis
yhat = model.predict(X_test)
mse = mean_squared_error(y_test, yhat)
print(f'mse: {mse}')

# Plot functions (real and approximated)
plt.plot(y_test)
plt.plot(yhat)
plt.legend(["Real y", ""])

# Plot MSE Evolution
plt.figure()
plt.plot(model.mse)
plt.title("MSE Evolution")
plt.xlabel("Epoch")
plt.ylabel("MSE")
```

```
mse: 3.3032665661654517
```

[49]:
```
Text(0, 0.5, 'MSE')
```



Real y
ŷ



MSE Evolution
MSE
Epoch

4 Problema 3 - Modelo de sistema dinâmico

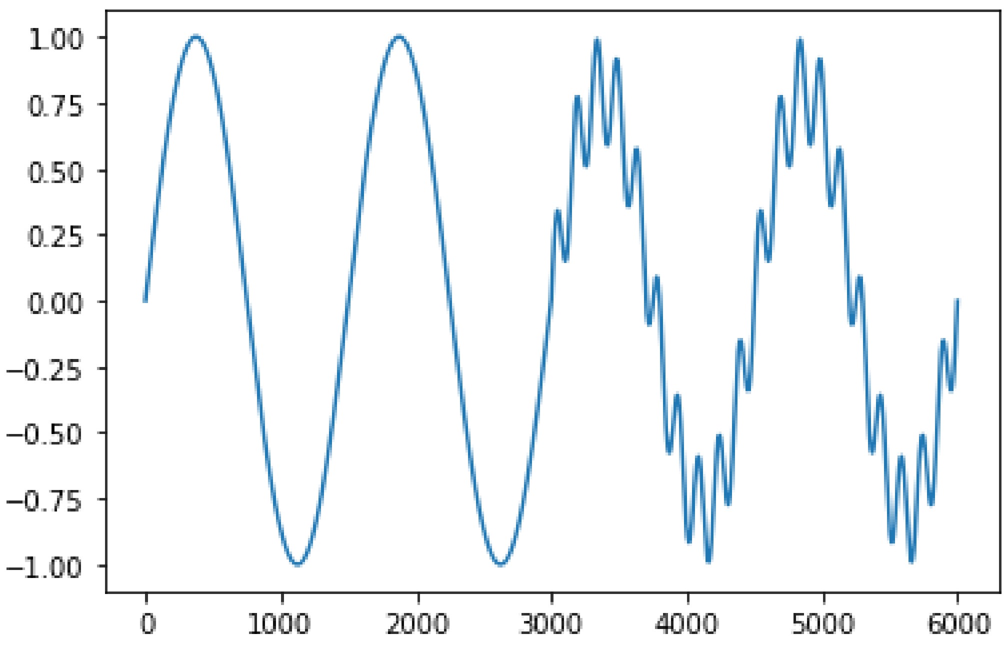
4.1 Geração dos dados

[50]:
```python
def g(x):
    num = x[0] * x[1] * x[2] * x[4] * (x[2] - 1) + x[3]
    den = 1 + x[2]**2 + x[3]**2
    return num / den
```

[51]:
```python
K = np.linspace(0, 1000, 6000)
u = []
for k in K:
    if k<=500:
        u.append(np.sin(2*np.pi * k / 250))
    else:
        u.append(0.8 * (np.sin(2*np.pi * k / 250)) + 0.2 * np.sin(2*np.pi * k/
↪25))
```

[52]:
```python
plt.plot(u)
```

[52]:
```
[<matplotlib.lines.Line2D at 0x7f9a76c75e80>]
```

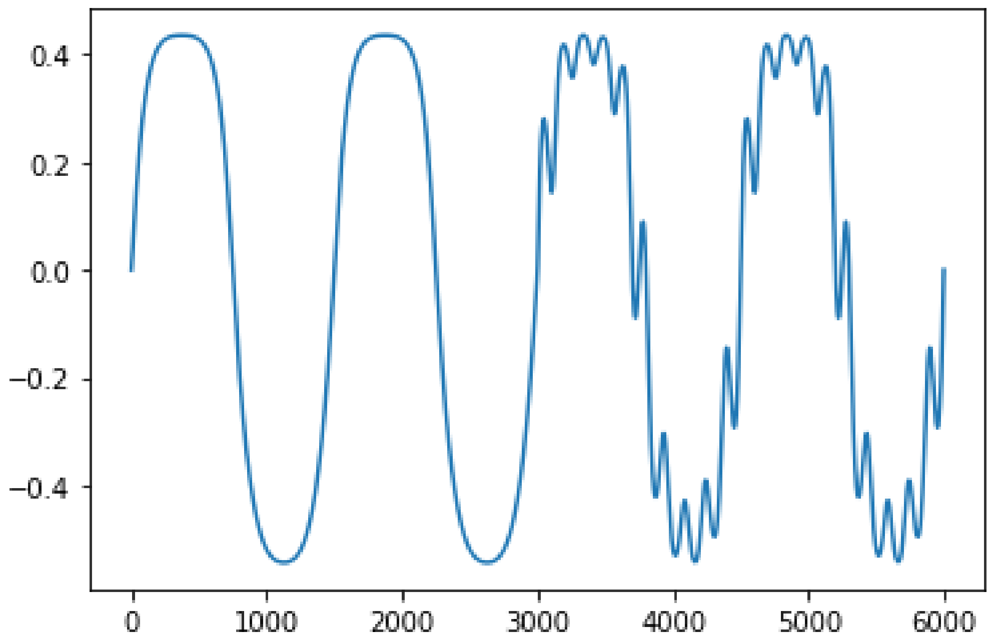


[53]:
```python
X=[]
y=[]
x = [0, 0, 0, u[0], 0]
X.append(x)
y.append(g(x))
x = [g(x), y[0], 0, u[1], u[0]]
```

```
X.append(x)
y.append(g(x))
for k in range(2, 6000):
    x = [g(x), y[k-1], y[k-2], u[k], u[k-1]]
    X.append(x)
    y.append(g(x))

X = np.array(X)
y = np.array(y)
```

[54]:
```
plt.plot(y)
```

[54]: [<matplotlib.lines.Line2D at 0x7f9a75dcffd0>]



4.2 Aplicação do Anfis desenvolvido

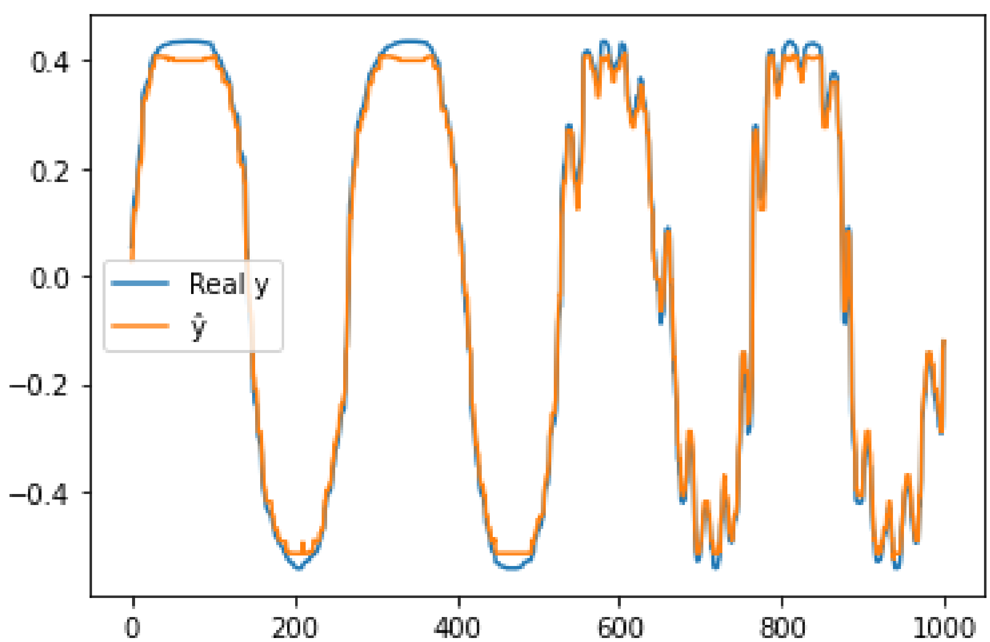
[55]:
```
# Train and Test split
test_idx = np.sort(np.random.randint(0, 6000, size=1000))
X_test = X[test_idx]
y_test = y[test_idx]
X_train = []
y_train = []

for idx in range(6000):
    if idx not in test_idx:
        X_train.append(X[idx])
```

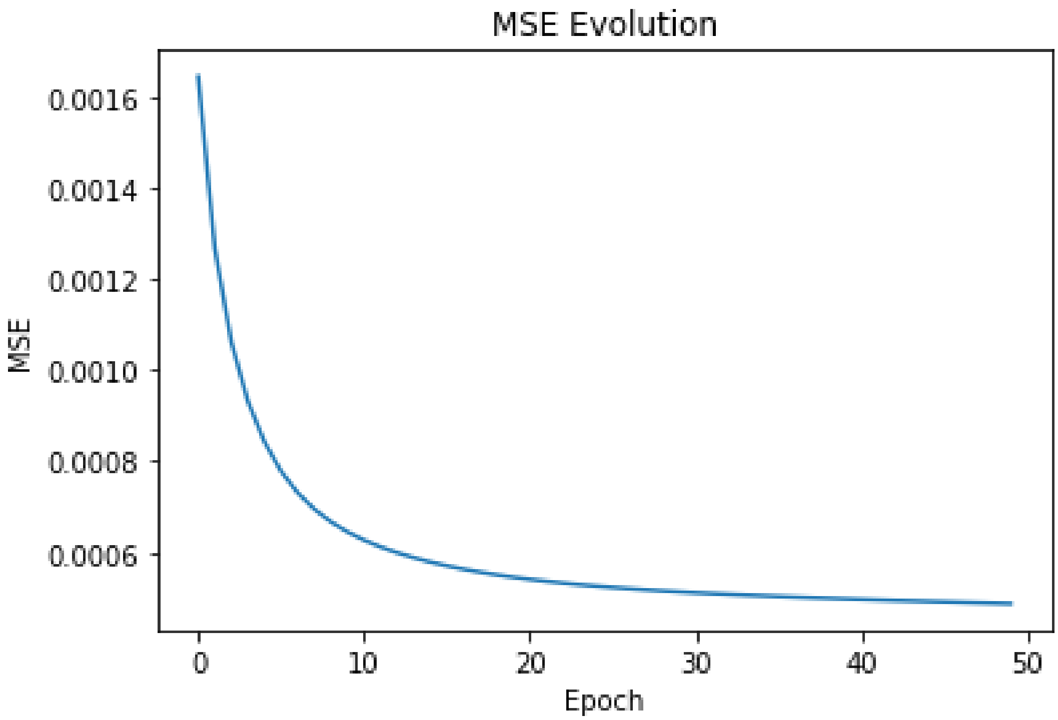
```
        y_train.append(y[idx])

X_train = np.array(X_train)
y_train = np.array(y_train)
```

[58]:
```
# Anfis
model = NFN(n_rules = 40, n_inputs = X_train.shape[1], n_epochs=50, lr=0.9)
model.fit(X_train, y_train)

# Eval fis
yhat = model.predict(X_test).reshape(-1, 1)
mse = mean_squared_error(y_test, yhat)
print(f'mse: {mse}')

# Plot functions (real and approximated)
plt.plot(y_test)
plt.plot(yhat)
plt.legend(["Real y", ""])

# Plot MSE Evolution
plt.figure()
plt.plot(model.mse)
plt.title("MSE Evolution")
plt.xlabel("Epoch")
plt.ylabel("MSE")
```

```
mse: 0.00042065748123988036
```

[58]:
```
Text(0, 0.5, 'MSE')
```





5 Problema 4 - Previsão de uma série temporal caótica

5.1 Geração de dados

Esse problema consiste em aproximação de uma série temporal caótica descrita pela seguinte função:

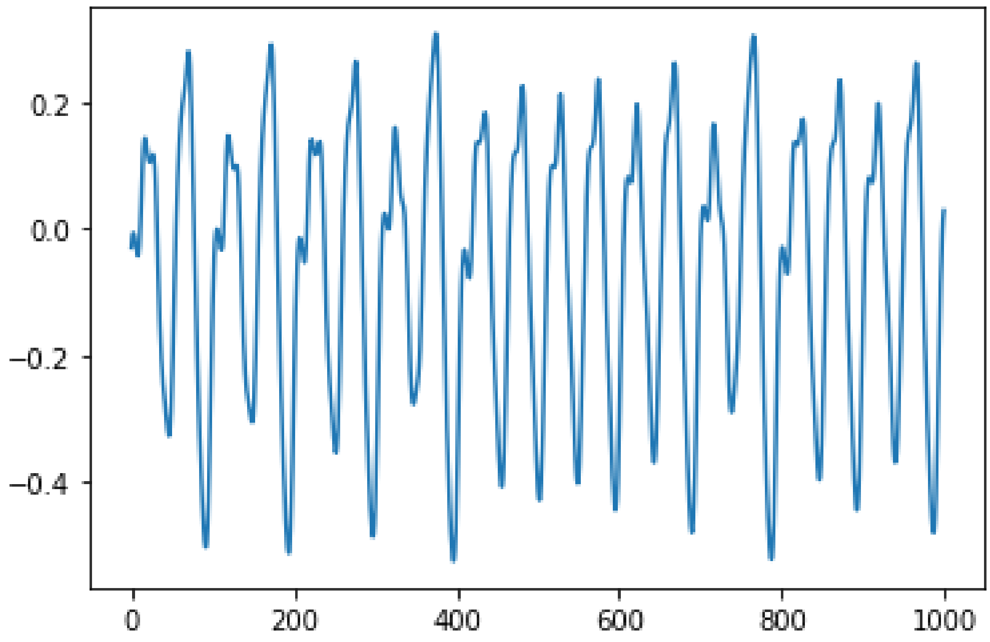
$\hat{x} = \frac{0.2x(t-\tau)}{1+x^{10}(t-\tau)} - 0.1x(t)$

As entradas desse problema são variáveis x(t), x(t-6), x(t-12) e x(t-18) e saída x(t+6). E esses dados x(t) foram obtidas da série temporal Mackey-Glass. Para a geração dos dados utilizou-se um intervalo de t=118 até 1117.

[59]:
```
# code from: https://github.com/mila-iqia/summerschool2015/blob/master/
↪rnn_tutorial/synthetic.py
def mackey_glass(sample_len=1000, tau=17, seed=None, n_samples = 1):
    delta_t = 10
    history_len = tau * delta_t
    # Initial conditions for the history of the system
    timeseries = 1.2

    if seed is not None:
        np.random.seed(seed)
```

```
    samples = []

    for _ in range(n_samples):
        history = collections.deque(1.2 * np.ones(history_len) + 0.2 * \
                                    (np.random.rand(history_len) - 0.5))
        # Preallocate the array for the time-series
        inp = np.zeros((sample_len,1))

        for timestep in range(sample_len):
            for _ in range(delta_t):
                xtau = history.popleft()
                history.append(timeseries)
                timeseries = history[-1] + (0.2 * xtau / (1.0 + xtau ** 10) - \
                             0.1 * history[-1]) / delta_t
            inp[timestep] = timeseries

        # Squash timeseries through tanh
        inp = np.tanh(inp - 1)
        samples.append(inp)
    return samples

serie = mackey_glass(sample_len=1130, tau=17, seed=None, n_samples = 1)[0]
```

[60]:
```
def x_hat(t, tau, x):
    x_hat = 0.2*x[t-tau]/(1+x^10*(t-tau))
    return x_hat

t = np.linspace(118, 1117, 1000)
X=[]
y=[]
for ti in t:
    x = [serie[int(ti)-18], serie[int(ti)-12], serie[int(ti)-6], serie[int(ti)]]
    X.append(x)
    y.append(serie[int(ti)+6])
plt.plot(y)

X = np.array(X)
y = np.array(y)
```



5.2 Aplicação do Anfis desenvolvido

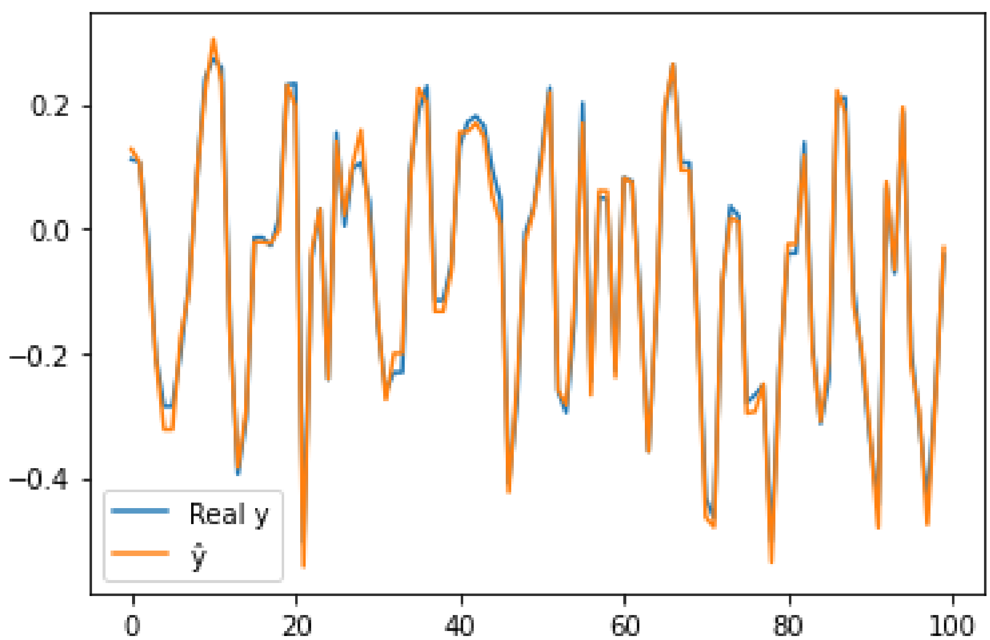
[61]:
```
# Train and Test split
test_idx = np.sort(np.random.randint(0, 1000, size=100))
X_test = X[test_idx]
X_test = X_test.reshape([X_test.shape[0], -1])
y_test = y[test_idx]
X_train = []
y_train = []

for idx in range(1000):
    if idx not in test_idx:
        X_train.append(X[idx])
        y_train.append(y[idx])

X_train = np.array(X_train)
X_train = X_train.reshape([X_train.shape[0], -1])
y_train = np.array(y_train)
```

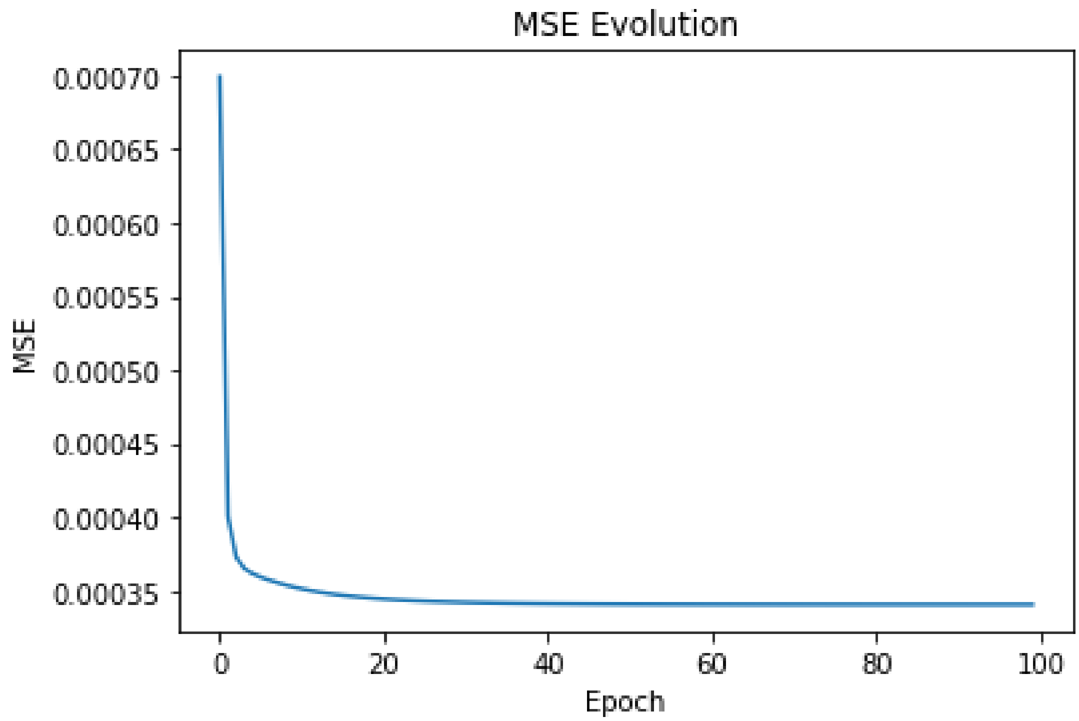
[62]:
```
# Anfis
model = NFN(n_rules = 50, n_inputs = 4, n_epochs=100, lr=0.9)
model.fit(X_train, y_train)

# Eval fis
yhat = model.predict(X_test).reshape(-1, 1)
mse = mean_squared_error(y_test, yhat)
```

```
print(f'mse: {mse}')

# Plot functions (real and approximated)
plt.plot(y_test)
plt.plot(yhat)
plt.legend(["Real y", ""])

# Plot MSE Evolution
plt.figure()
plt.plot(model.mse)
plt.title("MSE Evolution")
plt.xlabel("Epoch")
plt.ylabel("MSE")
```

```
mse: 0.0004075498362574023
```

[62]:
```
Text(0, 0.5, 'MSE')
```





6 Problema 5 - Problema de Regressão de um Data Set da UCI.

O data set escolhido para este exercício foi o "Airfoil Self-Noise". Essa base de dados contém 1503 instâncias. Foram utilizadas 5 variáveis de entrada e a variável a ser prevista foi a nível de pressão sonora, em decibéis..

6.1 Leitura e pré-processamento dos dados

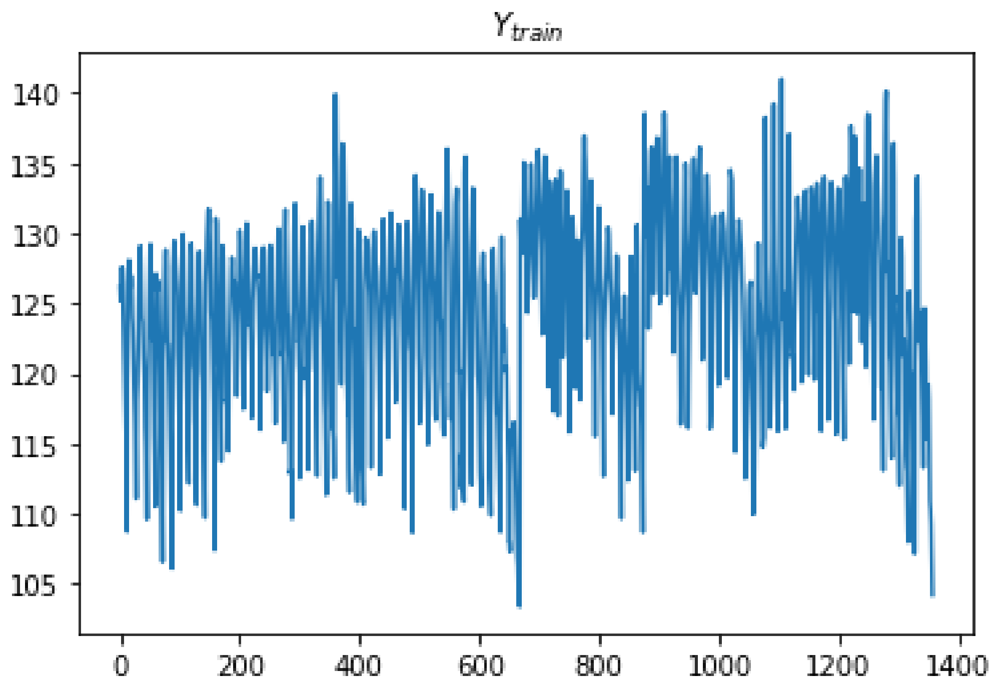
[67]:
```
dataset = pd.read_csv('data/airfoil_self_noise.dat', sep='\t', header=None)
dataset = dataset.replace("?", np.nan)
dataset = dataset.dropna()
dataset
```

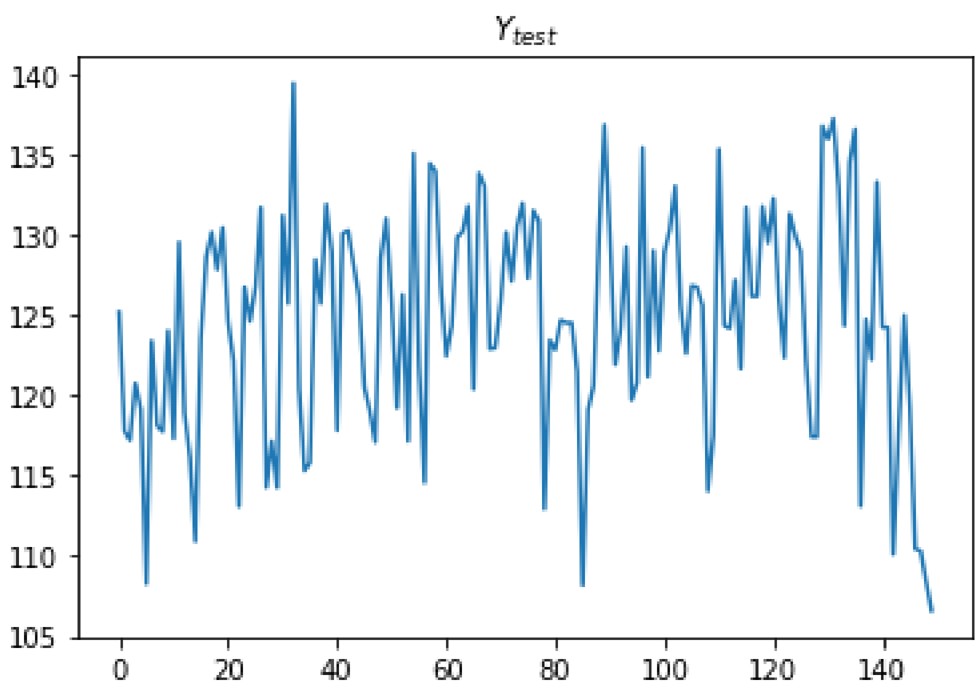
[67]:

	0	1	2	3	4	5
0	800	0.0	0.3048	71.3	0.002663	126.201
1	1000	0.0	0.3048	71.3	0.002663	125.201
2	1250	0.0	0.3048	71.3	0.002663	125.951
3	1600	0.0	0.3048	71.3	0.002663	127.591
4	2000	0.0	0.3048	71.3	0.002663	127.461
...	...	...	...	...	...	...
1498	2500	15.6	0.1016	39.6	0.052849	110.264
1499	3150	15.6	0.1016	39.6	0.052849	109.254
1500	4000	15.6	0.1016	39.6	0.052849	106.604

```
1501  5000  15.6  0.1016  39.6  0.052849  106.224
1502  6300  15.6  0.1016  39.6  0.052849  104.204

[1503 rows x 6 columns]
```

[68]:
```python
y = dataset[5].to_numpy()
X = dataset.drop([5], axis='columns').to_numpy()
normalizer = MinMaxScaler()
X = normalizer.fit_transform(X)
y = np.array(y.tolist())

test_idx = np.sort(np.random.randint(0, X.shape[0], size=int(X.shape[0]*0.1)))
X_test = X[test_idx]
y_test = y[test_idx]
X_train = []
y_train = []

for idx in range(X.shape[0]):
    if idx not in test_idx:
        X_train.append(X[idx])
        y_train.append(y[idx])
X_train = np.array(X_train)
y_train = np.array(y_train)

plt.plot(y_train)
plt.title('$Y_{train}$')
plt.figure()
plt.plot(y_test)
plt.title('$Y_{test}$')
```


Y_{train}
140
135
130
125
120
115
110
105
0
200
400
600
800
1000
1200
1400

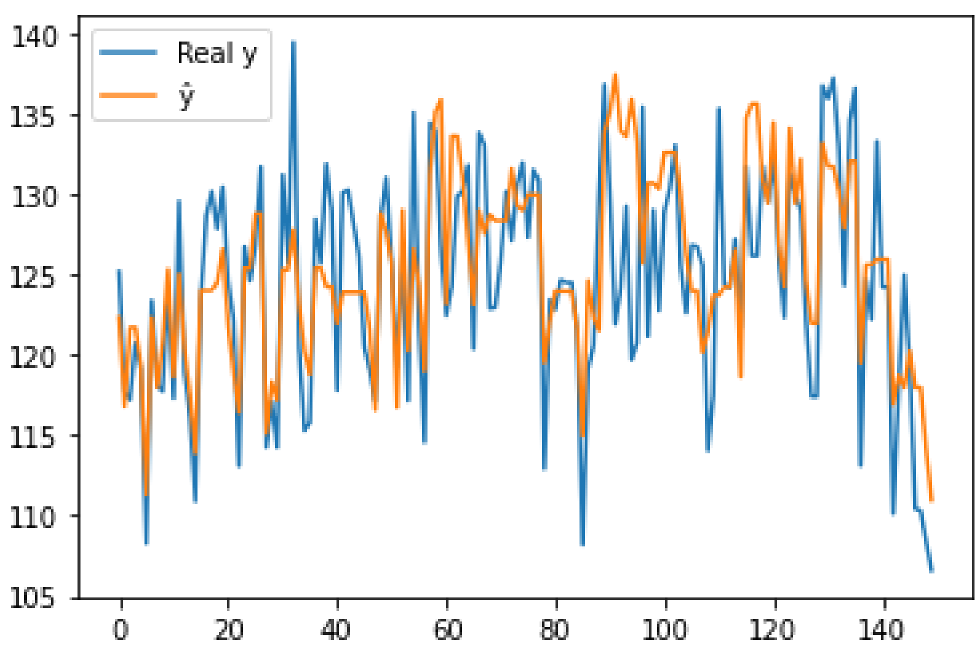

Y_{test}
140
135
130
125
120
115
110
105
0
20
40
60
80
100
120
140

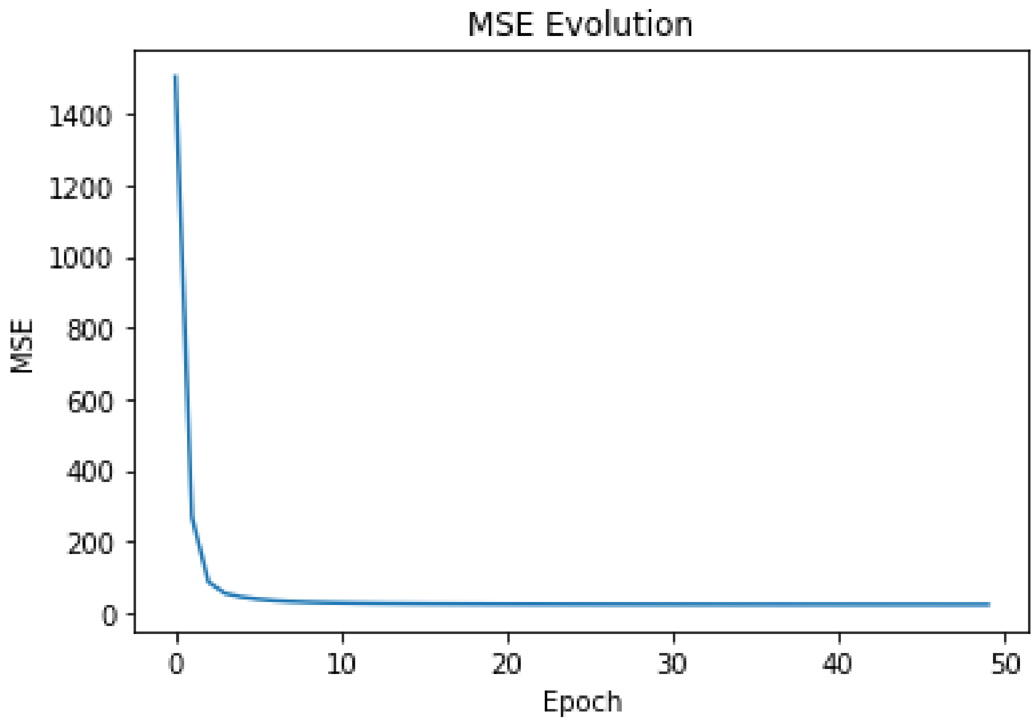
6.2 Aplicação do Anfis desenvolvido

[95]:
```
# Anfis
model = NFN(n_rules = 18, n_inputs = X_train.shape[1], n_epochs=50, lr=0.02)
model.fit(X_train, y_train)

# Eval fis
yhat = model.predict(X_test).reshape(-1, 1)
mse = mean_squared_error(y_test, yhat)
print(f'mse: {mse}')

# Plot functions (real and approximated)
plt.plot(y_test)
plt.plot(yhat)
plt.legend(["Real y", ""])

# Plot MSE Evolution
plt.figure()
plt.plot(model.mse)
plt.title("MSE Evolution")
plt.xlabel("Epoch")
plt.ylabel("MSE")
```

```
mse: 23.484143711747777
```

[95]:
```
Text(0, 0.5, 'MSE')
```




MSE Evolution
1400
1200
1000
800
600
400
200
0
MSE
0
10
20
30
40
50
Epoch