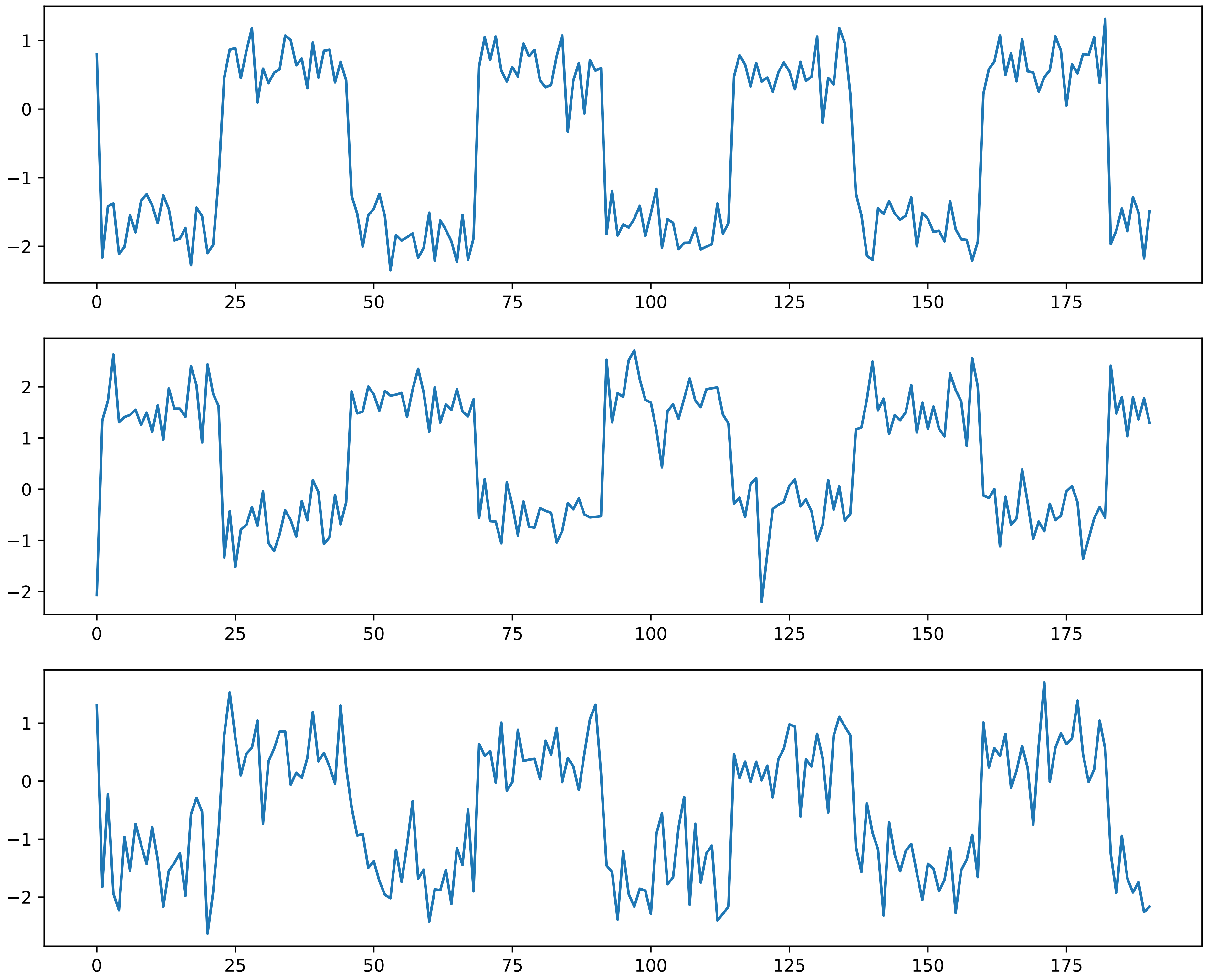
ResearcherCleveS

- github.com/ResearcherClevelS

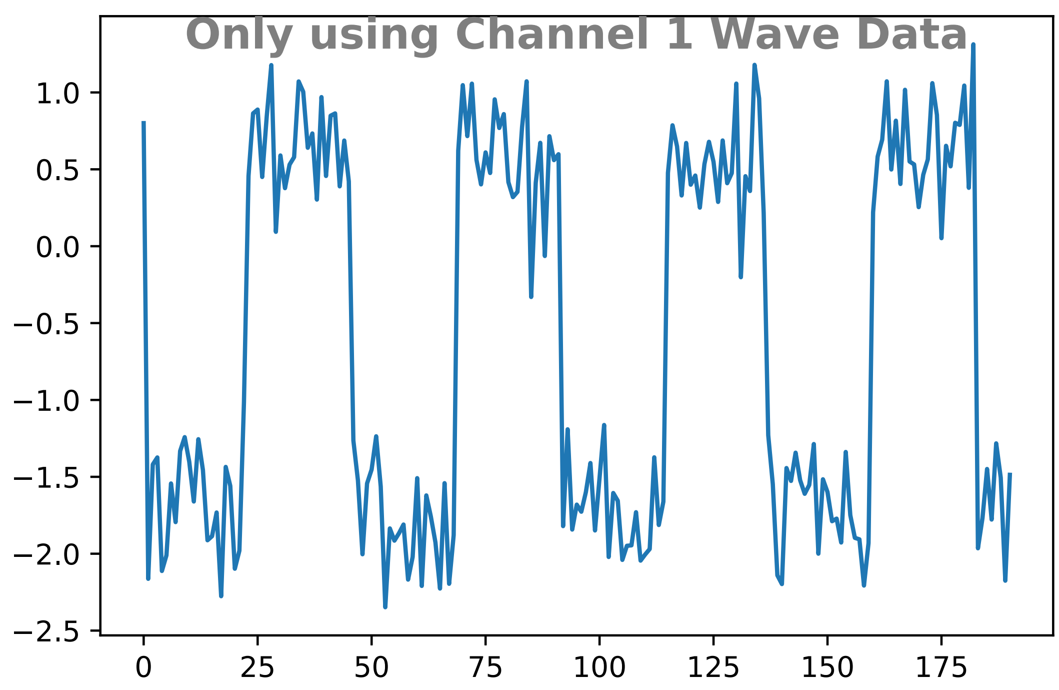
In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%config InlineBackend.figure_format = 'svg'
# import tensorflow.keras.models as tf
# from tensorflow.keras.models import Sequential
# from tensorflow.keras.layers import LSTM, Dense
# import sympy as sym
```

In [2]:
```
data = pd.read_csv('Closed Loop Forecast Data.csv')
fig, ax = plt.subplots(3, 1, figsize=(12, 10))
for i in range(0, data.columns.size):
    ax[i].plot(data[f"Channel {i+1}"]);
```



In [3]:
```
wav_data = data["Channel 1"].values
data["Channel 1"].values.shape, data.shape
plt.plot(wav_data);
plt.title("Only using Channel 1 Wave Data", color='tab:grey', y=.92, fontsize=15, fontweight='bold')
wav_data.shape
```

Out[3]: (191,)



In [4]:
```
wav_data
```

Out[4]:
```
array([ 0.8004, -2.1634, -1.4197, -1.3738, -2.1123, -2.0102, -1.5431,
       -1.7945, -1.3322, -1.2418, -1.4019, -1.6605, -1.2552, -1.4561,
       -1.9126, -1.886 , -1.7318, -2.2765, -1.4354, -1.5589, -2.0977,
       -1.98  , -1.0133,  0.4569,  0.8638,  0.8887,  0.4501,  0.8461,
        1.1779,  0.0934,  0.5902,  0.3774,  0.5305,  0.5793,  1.0717,
        1.0044,  0.6401,  0.7333,  0.3031,  0.9698,  0.4567,  0.8486,
        0.8637,  0.3892,  0.6872,  0.4217, -1.2639, -1.5234, -2.0036,
       -1.5431, -1.4527, -1.2363, -1.5629, -2.3482, -1.8354, -1.9151,
       -1.8671, -1.8102, -2.1685, -2.0213, -1.5085, -2.2096, -1.6208,
       -1.7591, -1.9264, -2.2267, -1.5411, -2.1957, -1.8791,  0.6215,
        1.0475,  0.716 ,  1.0573,  0.562 ,  0.402 ,  0.6101,  0.4761,
        0.9551,  0.7688,  0.8592,  0.4169,  0.3192,  0.3536,  0.7737,
        1.0724, -0.3303,  0.4124,  0.6724, -0.0638,  0.7154,  0.5598,
        0.5983, -1.8206, -1.1909, -1.843 , -1.6807, -1.7269, -1.599 ,
       -1.4102, -1.8488, -1.5163, -1.1628, -2.0213, -1.6051, -1.6556,
       -2.0403, -1.9484, -1.9456, -1.73  , -2.045 , -2.0052, -1.9695,
       -1.373 , -1.8134, -1.6612,  0.477 ,  0.7864,  0.6485,  0.3299,
        0.6714,  0.3999,  0.4596,  0.2509,  0.5335,  0.679 ,  0.5486,
        0.2879,  0.6877,  0.4097,  0.4751,  1.0577, -0.2018,  0.4554,
        0.3589,  1.1795,  0.9612,  0.2169, -1.2292, -1.547 , -2.1404,
       -2.1975, -1.4428, -1.5266, -1.3429, -1.5222, -1.6104, -1.5527,
       -1.2867, -1.9999, -1.5159, -1.599 , -1.7887, -1.7717, -1.9272,
       -1.3382, -1.749 , -1.8969, -1.9064, -2.2072, -1.9307,  0.2204,
        0.5829,  0.6932,  1.0724,  0.4988,  0.8164,  0.4047,  1.0173,
        0.5508,  0.532 ,  0.254 ,  0.4643,  0.5644,  1.0605,  0.8532,
        0.0521,  0.6529,  0.5195,  0.8027,  0.789 ,  1.0448,  0.3796,
        1.313 , -1.9647, -1.7674, -1.449 , -1.7779, -1.2823, -1.5052,
       -2.1755, -1.4869])
```

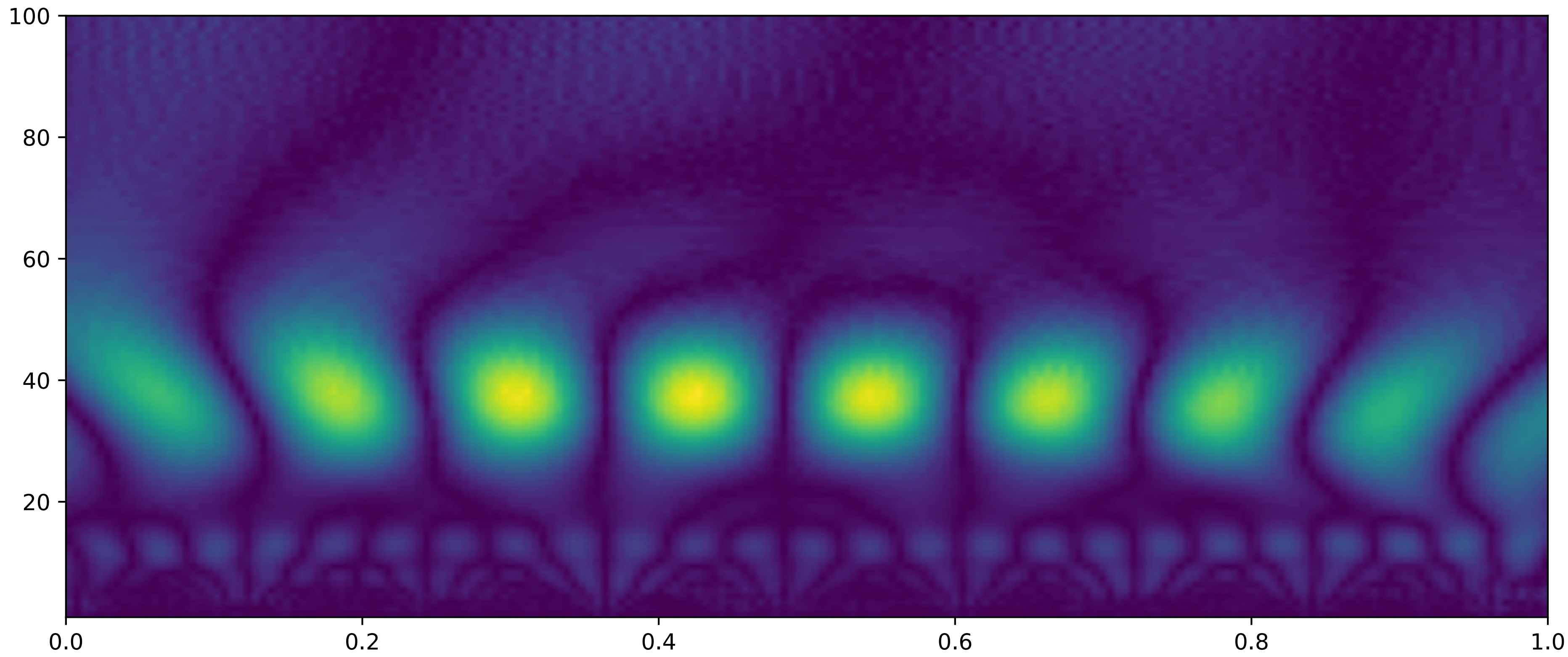
The filter design & operation $\left(\text{in the e.g. for sizes } \underline{\underline{\mathsf{H}}}^{12\times12}\cdot\underline{\mathsf{x}}^{12\times1}\right)$ are as follo

$$\begin{array}{c} \begin{matrix} h_0 & h_1 & h_2 & h_3 & h_4 & h_5 & 0 & 0 & \cdots & 0 & 0 \end{matrix} \\ \begin{bmatrix} -h_5 & h_4 & -h_3 & h_2 & -h_1 & h_0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & h_0 & h_1 & h_2 & h_3 & h_4 & h_5 & \cdots & 0 & 0 \\ 0 & 0 & -h_5 & h_4 & -h_3 & h_2 & -h_1 & h_0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & h_0 & h_1 & h_2 & h_3 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & -h_5 & h_4 & -h_3 & h_2 & \cdots & 0 & 0 \\ \vdots & & \ddots & \ddots & \ddots & & \ddots & \ddots & \ddots & \vdots & \vdots \\ h_4 & h_5 & \ddots & \ddots & \ddots & & \ddots & h_0 & h_1 & h_2 & h_3 \\ -h_1 & h_0 & \ddots & \ddots & \ddots & & \ddots & -h_5 & h_4 & -h_3 & h_2 \\ h_2 & h_3 & h_4 & h_5 & \ddots & \ddots & \ddots & \cdots & \ddots & h_0 & h_1 \\ -h_3 & h_2 & -h_1 & h_0 & \ddots & \ddots & \ddots & \cdots & \ddots & -h_5 & h_4 \end{bmatrix} \end{array} \cdot \begin{array}{c} x_0 \\ \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \\ x_{10} \\ x_{11} \end{bmatrix} \end{array} = \begin{array}{c} c_0 \\ \begin{bmatrix} d_0 \\ c_1 \\ d_1 \\ c_2 \\ d_2 \\ c_3 \\ d_3 \\ c_4 \\ d_4 \\ c_5 \\ d_5 \end{bmatrix} \end{array}.$$

We can think of the h_n's as a 2×6 array of low-pass filter (LPF) coefficients in the first row and high-pass coefficients (HPF) in t
Where h_n correspond with the Daubechies 6 LPF coefficients in the first row and h_n's negated flip in the second row.
These filter elements, h_n, shifted downward and over to the right by 2 display the downsampling by a factor of 2, which helps alor filter coefficients, effectively decomposes, extracts underlying information sought from the data vector. $\textsf{The wave data elements $x[n]$ are x_0 = 0.8004, x_1 = -2.1634, x_2 = -1.4197, $x3$= -1.3738,|dots|,,x{10}= -1.4019,x_{11}$\boxed{= -1.6605.}$
The output generated are the scales and wavelet coefficients denoted c_n and d_n, respectively.

Its Continuous wavelet transform (CWT) version

In [22]:
```
import pywt

# Generate a sample time series
time = np.linspace(0, 1, 1000, endpoint=False)
signal = wav_data

# Perform the Continuous Wavelet Transform (CWT)
wavelet = 'morl'  # Choose a wavelet function (e.g., 'morl', 'gaus1', 'cgau8')
scales = np.arange(1, 101)  # Define the scales for the CWT
coefficients, frequencies = pywt.cwt(signal, scales, wavelet, 1/len(time))

plt.figure(figsize=(12, 5))
plt.imshow(np.abs(coefficients), extent=[0, 1, 1, 100], aspect='auto',
               origin='lower', cmap='viridis')
plt.show()
```



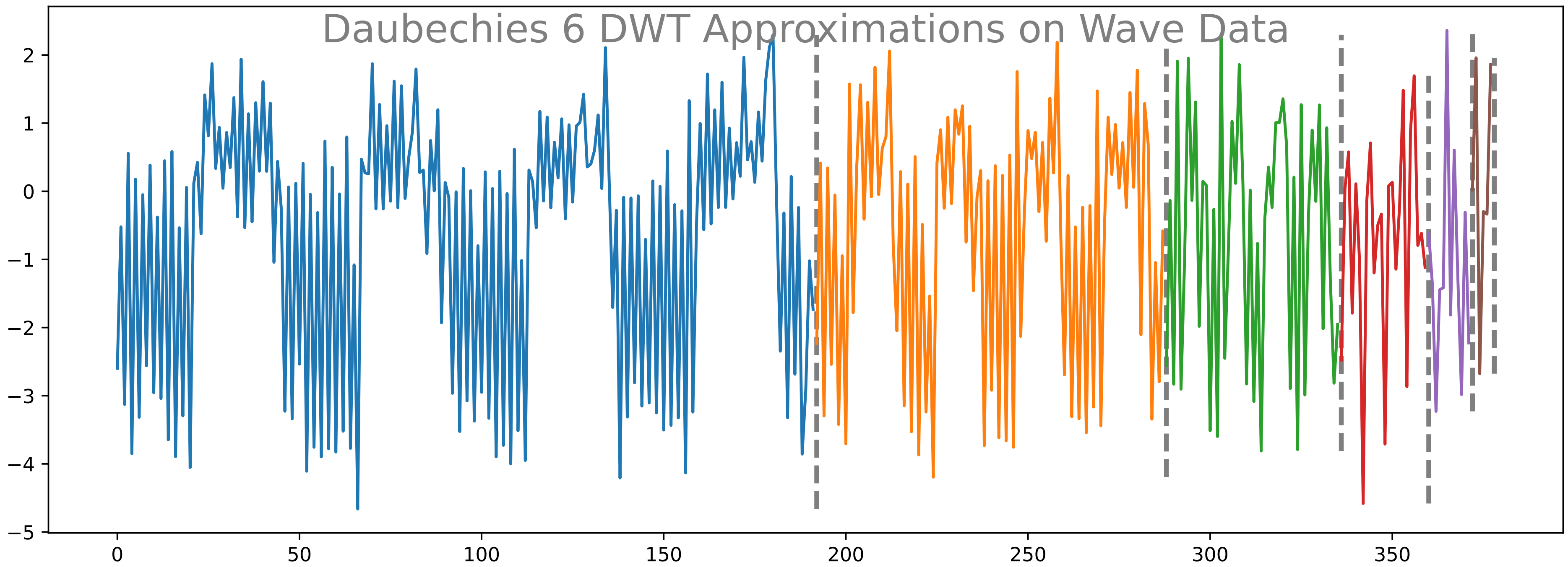
Additional image visual of the frequency against time coeficients.

In [5]:
```
N = 192
wav_flt_lst = []
inv_wav_flt_lst = []
for _ in range(0, 6):
    wav_fltr = np.zeros((N, N))
    wav_flt_lst.append(wav_fltr)
    N = N // 2
[np.shape(wav_flt_lst[i]) for i in range(0, 6)] # Only want up to range 6, the number of coeffs.
```

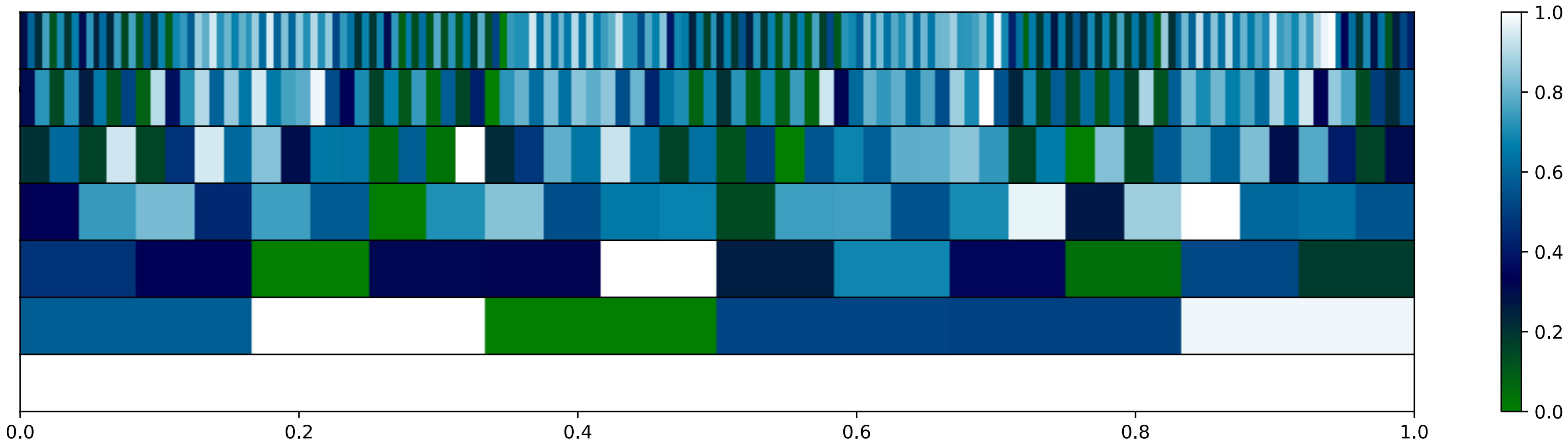
Out[5]:
```
[(192, 192), (96, 96), (48, 48), (24, 24), (12, 12), (6, 6)]
```

In [250…

```
daub6_low = [0.47046721, 1.14111692, 0.650365, -0.19093442, -0.12083221, 0.0498175]
daub6_high = [(-1)**j * i for j, i in enumerate(daub6_low.copy()[::-1])]
fltr = [daub6_low, daub6_high]
conv_flt_wav_dat_lst = []
wave_dat = wav_data.copy()
for i in range(0, len(wav_flt_lst)):
    for j in range(0, len(wav_flt_lst[i])-4, 2):
        wav_flt_lst[i][-4:-3, -4:] = [fltr[0][i] for i in range(4)]
        wav_flt_lst[i][-4:-3, :2 ] = [fltr[0][i] for i in range(5,3,-1)]
        wav_flt_lst[i][-3:-2, -4:] = [fltr[1][i] for i in range(4)]
        wav_flt_lst[i][-3:-2, :2 ] = [fltr[1][i] for i in range(5,3,-1)]
        wav_flt_lst[i][-2:-1, -2:] = [fltr[0][i] for i in range(2)]
        wav_flt_lst[i][-2:-1, :4 ] = [fltr[0][i] for i in range(5,1,-1)]
        wav_flt_lst[i][-1:, -2:] = [fltr[1][i] for i in range(2)]
        wav_flt_lst[i][-1:, :4 ] = [fltr[1][i] for i in range(5,1,-1)]
        wav_flt_lst[i][j:j+2, j:j+len(daub6_low)] = fltr
    if i == 0:
        wave_dat = np.append(wav_data.copy(), np.zeros(1))
    else:
        wave_dat = wav_data.copy()[::2**i]
    conv_flt_wav_dat_lst.append(wav_flt_lst[i] @ wave_dat)

plt.figure(figsize=(14, 5))
n, N = 0, len(conv_flt_wav_dat_lst[0])
for i in range(0, len(conv_flt_wav_dat_lst)):
    plt.plot(range(n, N), conv_flt_wav_dat_lst[i])
    plt.plot([N, N], [conv_flt_wav_dat_lst[i].min(), conv_flt_wav_dat_lst[i].max()],
             color='tab:grey', linestyle='--', linewidth=2.5);
    if i == 5:
        break
    n += conv_flt_wav_dat_lst[i].size
    N += conv_flt_wav_dat_lst[i+1].size
plt.title("Daubechies 6 DWT Approximations on Wave Data", color='tab:grey', y=.91, fontsize=20);

# import matplotlib.colors as colors
fig, ax = plt.subplots(7, 1, figsize=(17, 4))
for j in range(len(ax)-1):
    N = conv_flt_wav_dat_lst[j].size
    im = ax[j].imshow(conv_flt_wav_dat_lst[j][np.newaxis, :],#==.reshape(1, N),
                      aspect="auto", cmap='ocean');

    plt.rcParams["axes.grid"] = False
    plt.subplots_adjust(wspace=0, hspace=0)
    fig.suptitle("Six-Level Daubechies 6 (Daub6) Transform of Channel 1 Wave Data", fontweight='bold',
                 fontsize=19, x=.435, color='tab:grey');
    # ax[j].set_xlim(0, conv_flt_wav_dat_lst[j].size)
    if j == 7: # Insignificant.
        break
[ax[j].set_yticks([]) for j in range(0, 7)]
plt.colorbar(plt.cm.ScalarMappable(norm=None,
                  cmap="ocean"),
    ax=ax,
location="right");
```

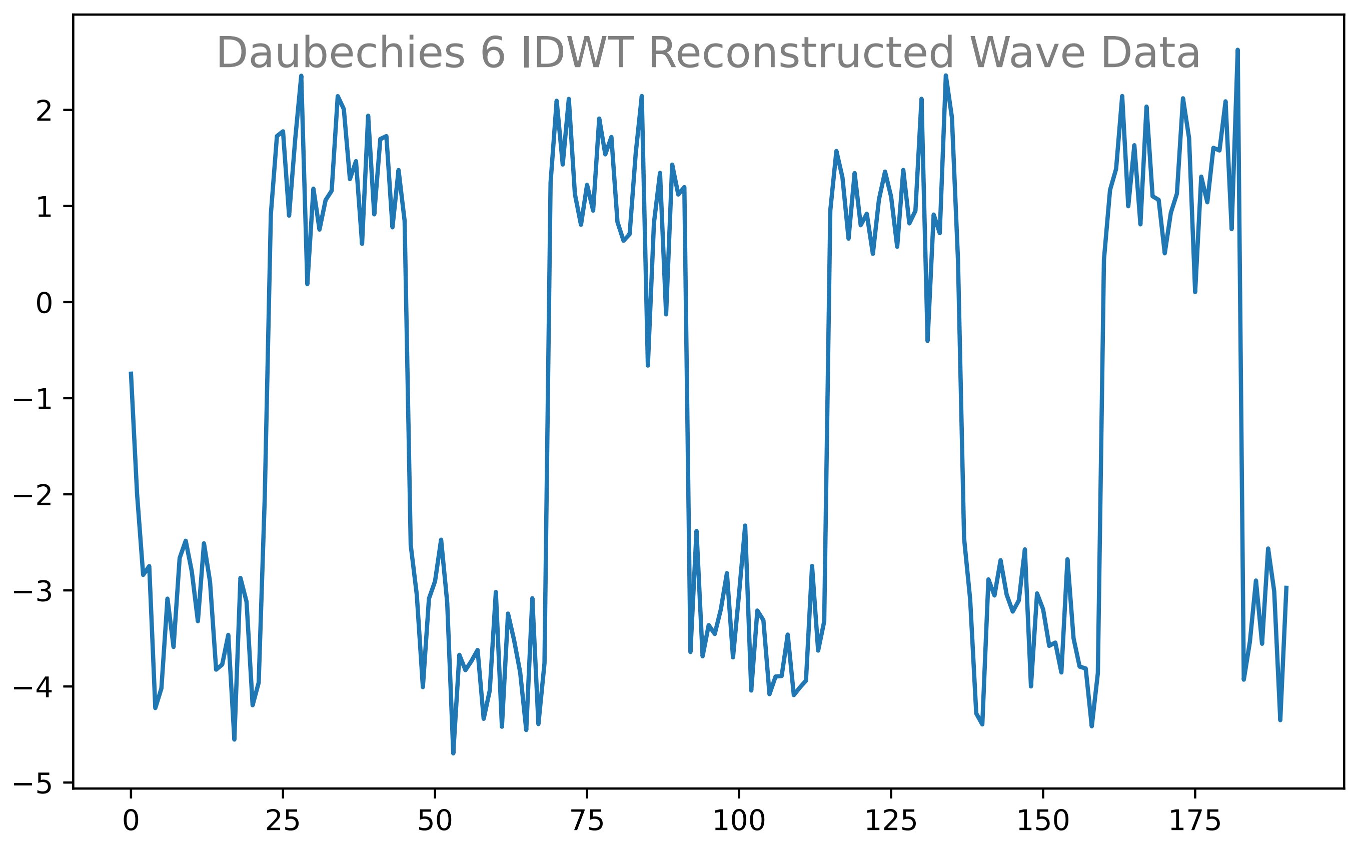


Six-Level Daubechies 6 (Daub6) Transform of Channel 1 Wave Data



In [7]:

```
# Reconstruction Inv. wavelet transform (IDWT)
N = 384
time_series_rec = np.zeros(N)
# wav_data_lst = []
flt_lst = []
recon_inv_flt_lst = []
for _ in range(0, 7):
    # wav_data_lst.append(wav_data.copy())
    flt_lst.append(np.zeros((N, N)))
    recon_inv_flt_lst.append(np.zeros((N, N)))
    N = N // 2
[(flt_lst[i].shape, recon_inv_flt_lst[i].shape) for i in range(0, 7)]

time_series_rec_lst = []
for i in range(0, 7):
    if i == 0:
        time_series_rec[::2] = np.append(wav_data.copy()[::2**i], np.zeros(1))
    else:
        time_series_rec[::2] = wav_data.copy()[::2**i]
    time_series_rec_lst.append(time_series_rec)
    time_series_rec = np.zeros(time_series_rec.shape[0] // 2)

conv_flt_t_series = []
recon_final_lst = []
for i in range(0, len(flt_lst)):
    for j in range(0, len(flt_lst[i])-4, 2):
        flt_lst[i][-4:-3, -4:] = [fltr[0][i] for i in range(4)]
        flt_lst[i][-4:-3, :2 ] = [fltr[0][i] for i in range(5,3,-1)]
        flt_lst[i][-3:-2, -4:] = [fltr[1][i] for i in range(4)]
        flt_lst[i][-3:-2, :2 ] = [fltr[1][i] for i in range(5,3,-1)]
        flt_lst[i][-2:-1, -2:] = [fltr[0][i] for i in range(2)]
        flt_lst[i][-2:-1, :4 ] = [fltr[0][i] for i in range(5,1,-1)]
        flt_lst[i][-1:, -2:] = [fltr[1][i] for i in range(2)]
        flt_lst[i][-1:, :4 ] = [fltr[1][i] for i in range(5,1,-1)]
        flt_lst[i][j:j+2, j:j+len(daub6_low)] = fltr
        recon_inv_flt_lst[i] = flt_lst[i].copy().T
    conv_flt_t_series.append(flt_lst[i] @ time_series_rec_lst[i])
    recon_final_lst.append(recon_inv_flt_lst[i] @ conv_flt_t_series[i])


plt.figure(figsize=(8, 5))
plt.plot(recon_final_lst[0][:-2:2]);
plt.title("Daubechies 6 IDWT Reconstructed Wave Data", color='tab:grey', y=.91, fontsize=15);
```

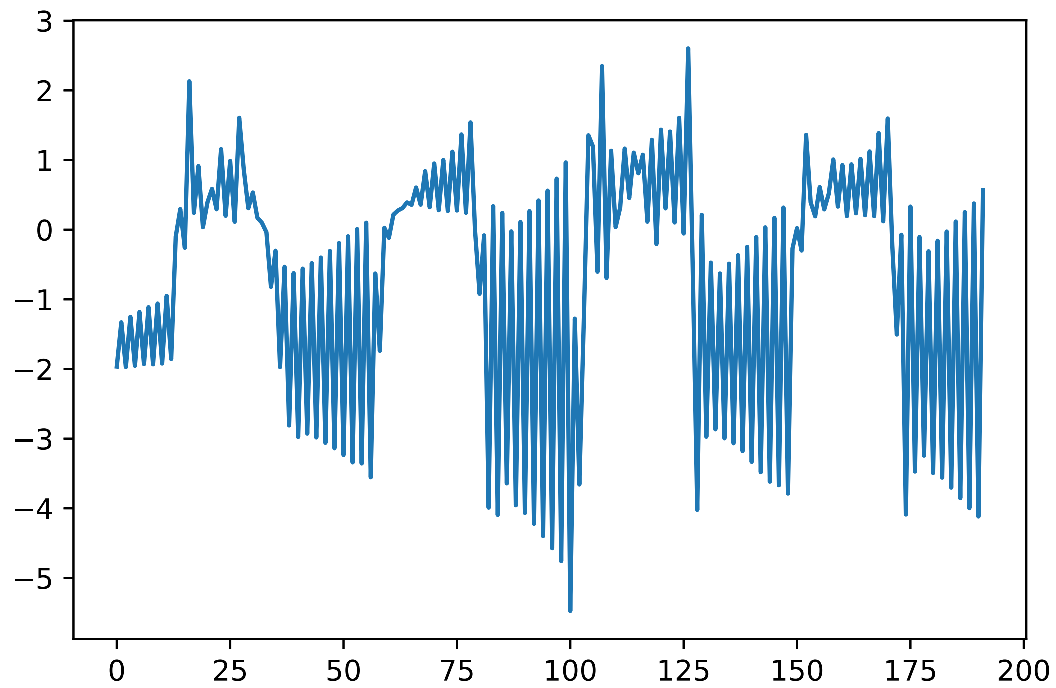


In [8]:
```python
# Prepare data for LSTM (sequence length of 3)
def prepare_data(data, sequence_length):
    x, y = [], []
    for i in range(len(data) - sequence_length):
        x.append(data[i:i+sequence_length])
        y.append(data[i+sequence_length])
    return np.array(x), np.array(y)

# Decompose the wav_data into low & high- frequency scales & wavelet coeffs first.
# Then feed as input the separated data into the LSTM or GRU model to train.
# Then implement the closed loop feedback forecast. Finally, reconstruct the
# WT coeffs approximations based predictions.

sequence_length = 30
# x, y = prepare_data(data, sequence_length)
x, y = prepare_data(conv_flt_wav_dat_lst[0], sequence_length)
x = x.reshape(x.shape[0], x.shape[1], 1)
```

In [ ]:
```python
# Build LSTM model
model = np.Sequential([
    LSTM(50, activation='relu', input_shape=(sequence_length, 1)),
    Dense(1)
])
model.compile(optimizer='adam', metrics=['mse'], loss='mse')

# Train the model
# model.fit(x, y, epochs=1000 // 2, verbose=0); # May need more epochs.
model.fit(x, y, epochs=1000 // 2, verbose=0); # May need more epochs.
```

In [ ]:
```python
# Closed-loop forecasting
n_predictions = 192
forecast_input = x[-1]  # Last sequence from the training data
predictions = []

for _ in range(n_predictions):
    # Reshape forecast input for the model
    forecast_input = forecast_input.reshape((1, sequence_length, 1))

    # Make prediction
    forecast_output = model.predict(forecast_input, verbose=0)[0] # verbose=1,2 great options.

    # Append prediction to the list
    predictions.append(forecast_output[0])

    # Update forecast input for the next iteration
    forecast_input = np.append(forecast_input[0][1:], forecast_output)

# Inverse transform predictions
# predictions = np.array(predictions) * 100
print("Predictions:", predictions)
```

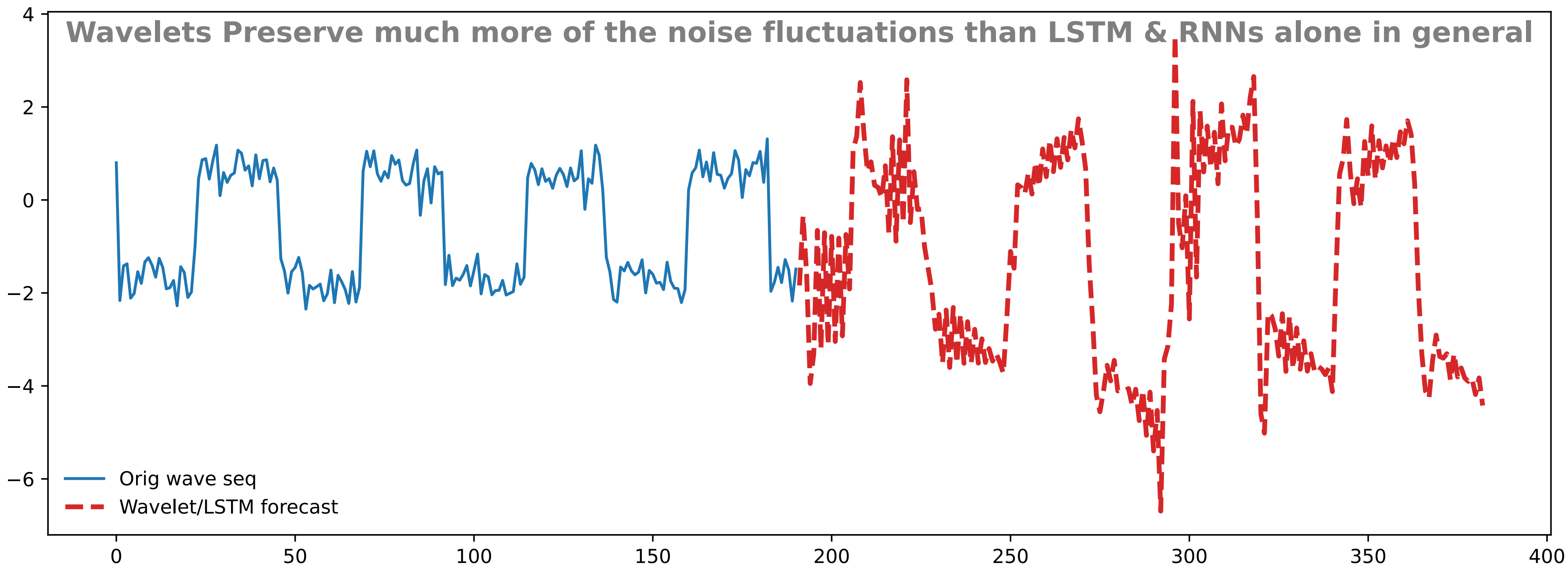
In [9]:
```python
predictions = pd.read_csv('Predictions - Wavelets LSTM Closed Loop Forecast.csv')
preds_1 = predictions["Predictions 1"].values
plt.plot(preds_1);
```



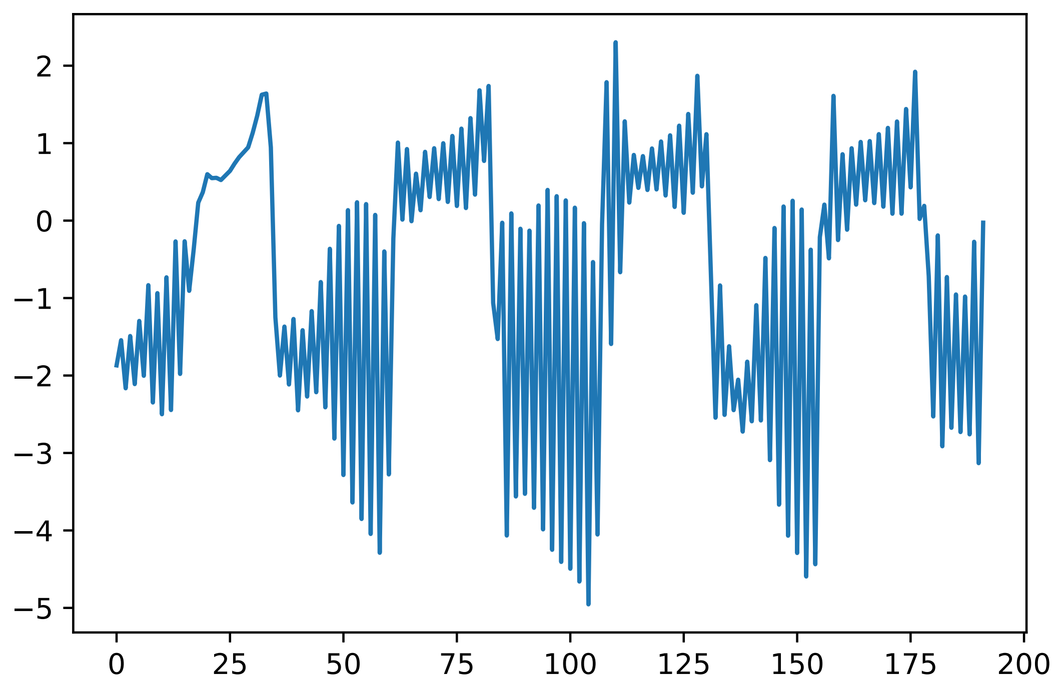
Closed Loop Forecasting where it pertains to financial data

- it is crucial to preserve its noise flucuations containing information.

In [10]:
```python
# Perform the reconstruction of the predictions based on wavelet approximations.
recon_sig_approx = recon_inv_flt_lst[1] @ preds_1
plt.figure(figsize=(14, 5))
plt.plot(wav_data, label='Orig wave seq');
plt.plot(range(wav_data.size, wav_data.size+recon_sig_approx.size), recon_sig_approx, color='tab:red',
         linestyle='--', linewidth=2.5, label='Wavelet/LSTM forecast');
plt.title("Wavelets Preserve much more of the noise fluctuations than LSTM & RNNs alone in general",
          color='tab:grey', y=.92, fontsize=14.75, fontweight='bold');
plt.legend(frameon=False, loc='lower left');
```



In [11]:
```python
preds_2 = predictions["Predictions 2"].values
plt.plot(preds_2);
```



In [12]:
```python
plt.figure(figsize=(14, 5))
# Perform the reconstruction of the predictions based on wavelet approximations.
rec_signal = recon_inv_flt_lst[1] @ preds_2
plt.plot(wav_data, label='Orig wave seq');
plt.plot(range(wav_data.size, wav_data.size+rec_signal.size), rec_signal, color='tab:red',
         linestyle='--', linewidth=2.5, label='Wavelet/LSTM forecast');
plt.title("Wavelets Preserve much more of the noise fluctuations than LSTM & RNNs alone in general",
          color='tab:grey', y=.92, fontsize=14.75, fontweight='bold');
plt.legend(frameon=False, loc='lower left');
```