

```
In [138... import numpy as np
import warnings
import pandas as pd
import matplotlib.pyplot as plt
from scipy.optimize import minimize
from scipy.optimize import differential_evolution, shgo, dual_annealing, basinhopping
seed = 123
```

Project: One-Mass Oscillator Optimization

Introduction

In this project, you will apply various optimization algorithms to fit a one-mass oscillator model to real-world data. The objective is to minimize the sum of the squared residuals between the model predictions and the observed amplitudes of a one-mass oscillator system across different frequencies.

One-Mass Oscillator Model

The one-mass oscillator is characterized by the following equation, representing the amplitudes of the system:

$$V(\omega) = \frac{F}{\sqrt{(1 - \nu^2)^2 + 4D^2\nu^2}}$$

Here,

- ω represents the angular frequency of the system,
- ν is the ratio of the excitation frequency to the natural frequency ($\nu = \frac{\omega_{\text{err}}}{\omega_{\text{eig}}}$),
- D is the damping ratio,
- F is the force applied to the system.

The goal of the project is to determine the optimal values for the parameters ω_{eig} , D , and F that result in the best fit of the one-mass oscillator model to the observed amplitudes.

Load the real world data

- we have two different measurements
- J represents the measured frequencies
- N represents the measured amplitudes

```
In [139... df1 = pd.read_pickle("df1.pkl")
df2 = pd.read_pickle("df2.pkl")
# Printing the lengths of the DataFrames
print("Length of df1:", len(df1))
print("Length of df2:", len(df2))
```

Length of df1: 33
Length of df2: 66

Low amplitudes distort the fit and are negligible therefore we define a lower threshold for N

```
In [140... threshold = 0.4
df1.sort_values("N")
max_N = max(df1["N"])
df1 = df1[df1["N"]>=threshold*max_N]

# checking the lengths of the DataFrames again
print("Length of df1:", len(df1))
print("Length of df2:", len(df2))
```

Length of df1: 31
Length of df2: 66

We extract the frequency value for maximum value of the amplitude. This serves as the initial value for one decision variable.

```
In [141... df_max=df1[df1["N"]==max(df1["N"])]
initial_0eig = df_max["J"].values[0]
max_N = df_max["N"].values[0]
```

We also have to define the other two initial guesses

```
In [142... initial_D = 0.006
initial_F = 0.120

initial_values = [initial_0eig, initial_D, initial_F]
```

Additionally we define the bounds for the decision variables

```
In [143... min_0err = min(df1["J"])
max_0err = max(df1["J"])

In [144... bounds = [(min_0err, max_0err), (0, 0.03), (0, 1)]
```

Then we define the objective function

```
In [145... def one_mass_oscillator(params, 0err) -> np.ndarray:
    # returns amplitudes of the system
    # Defines the model of a one mass oscillator
    0eig, D, F = params
    nue = 0err / 0eig
    V = F / (np.sqrt((1 - nue**2) ** 2 + (4 * D**2 * nue**2)))
    return V

In [146... def objective_function(params, 0err, amplitudes) -> np.ndarray:
    # objective function to compare calculated and real amplitudes
    return np.sum((amplitudes - one_mass_oscillator(params, 0err)) ** 2)
```

We define the options and start the optimization process

```
In [147... options = {
    "maxfun": 100000, #Maximum Function Evaluation
    "ftol": 1e-9,     # Function Tolerance
    "xtol": 1e-9,     #Variable Tolerance
    "stepmx": 10,     #Controls Maximum Step size
    "eta": 0.25,      #Controls relative Step Size
    "gtol": 1e-5}     #Gradient Tolerance
```

```
In [148... J = np.array(df1["J"]) # measured frequency
N = np.array(df1["N"]) # measured amplitude
```

```
In [149... result = minimize(
    objective_function,
    initial_values,
    args=(J, N),
    method='Nelder-Mead',
    bounds=bounds,
    options=options)
```

```
/tmp/ipykernel_975535/2959858538.py:1: OptimizeWarning: Unknown solver options: maxfun, ftol, xtol, stepmx, eta, gtol
result = minimize(
```

Then we can observe the results

```
In [150... # map optimized values to variables
resonant_frequency = result.x[0]
D = result.x[1]
F = result.x[2]
# predict the resonant amplitude with the fitted one mass oscillator.
X_pred = np.linspace(min_0err, max_0err, 1000)
ypred_one_mass_oscillator = one_mass_oscillator(result.x, X_pred)
resonant_amplitude = max(ypred_one_mass_oscillator)
```

```
In [151... result
```

```
Out[151]: message: Optimization terminated successfully.
          success: True
          status: 0
           fun: 53.54144061205875
            x: [ 8.148e+03  7.435e-04  2.153e-02]
           nit: 93
          nfev: 169
    final_simplex: (array([[ 8.148e+03,  7.435e-04,  2.153e-02],
                           [ 8.148e+03,  7.435e-04,  2.153e-02],
                           [ 8.148e+03,  7.435e-04,  2.153e-02],
                           [ 8.148e+03,  7.435e-04,  2.153e-02]]), array([
5.354e+01,  5.354e+01,  5.354e+01,  5.354e+01]))
```

Finally, we can plot the optimized fit and the real values

```
In [152... plt.scatter(
    df1["J"],
    df1["N"],
```

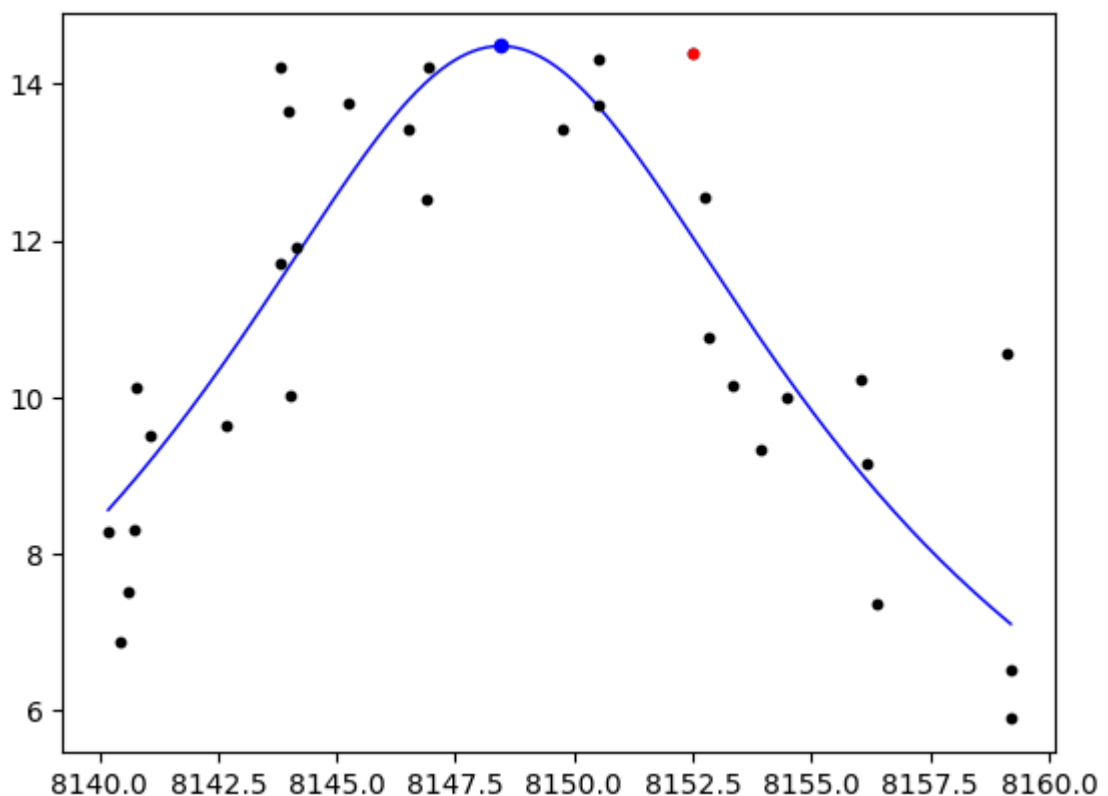
```

        color="black",
        label="Spektralkpunkte filtered",
        zorder=5,
        s=10,
    )
    # color the max amplitude point red
    plt.scatter(
        initial_0eig,
        max_N,
        color="red",
        label="Max Amplitude",
        zorder=5,
        s=10,
    )

    plt.plot(
        X_pred,
        ypred_one_mass_oscillator,
        label="Alpha",
        color="blue",
        linewidth=1,
    )
    plt.scatter(
        resonant_frequency,
        resonant_amplitude,
        color="blue",
        label="Max Curve Fit",
        zorder=10,
        s=20,
    )

```

Out[152]: <matplotlib.collections.PathCollection at 0x14a73828a810>



Task for the Project Work

Optimization of First Data Frame

Using Global Optimizers

Using Dual Annealing

```
In [153... result = dual_annealing(
    objective_function,
    bounds=bounds,
    args=(J, N),
    maxiter=1000, # Maximum number of iterations
    seed=123, # Seed for reproducibility
)

# Plotting
plt.scatter(
    df1["J"],
    df1["N"],
    color="black",
    label="Filtered Spectral Points",
    zorder=5,
    s=10,
)

# color the max amplitude point red
plt.scatter(
    initial_0eig,
    max_N,
    color="red",
    label="Max Amplitude",
    zorder=5,
    s=10,
)

plt.plot(
    X_pred,
    ypred_one_mass_oscillator,
    label="Alpha",
    color="blue",
    linewidth=1,
)

plt.scatter(
    resonant_frequency,
    resonant_amplitude,
    color="blue",
    label="Max Curve Fit",
    zorder=10,
    s=20,
)

plt.legend()
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.title("Dual Annealing Optimization")
plt.show()

print("Optimized Parameters:")
```

```

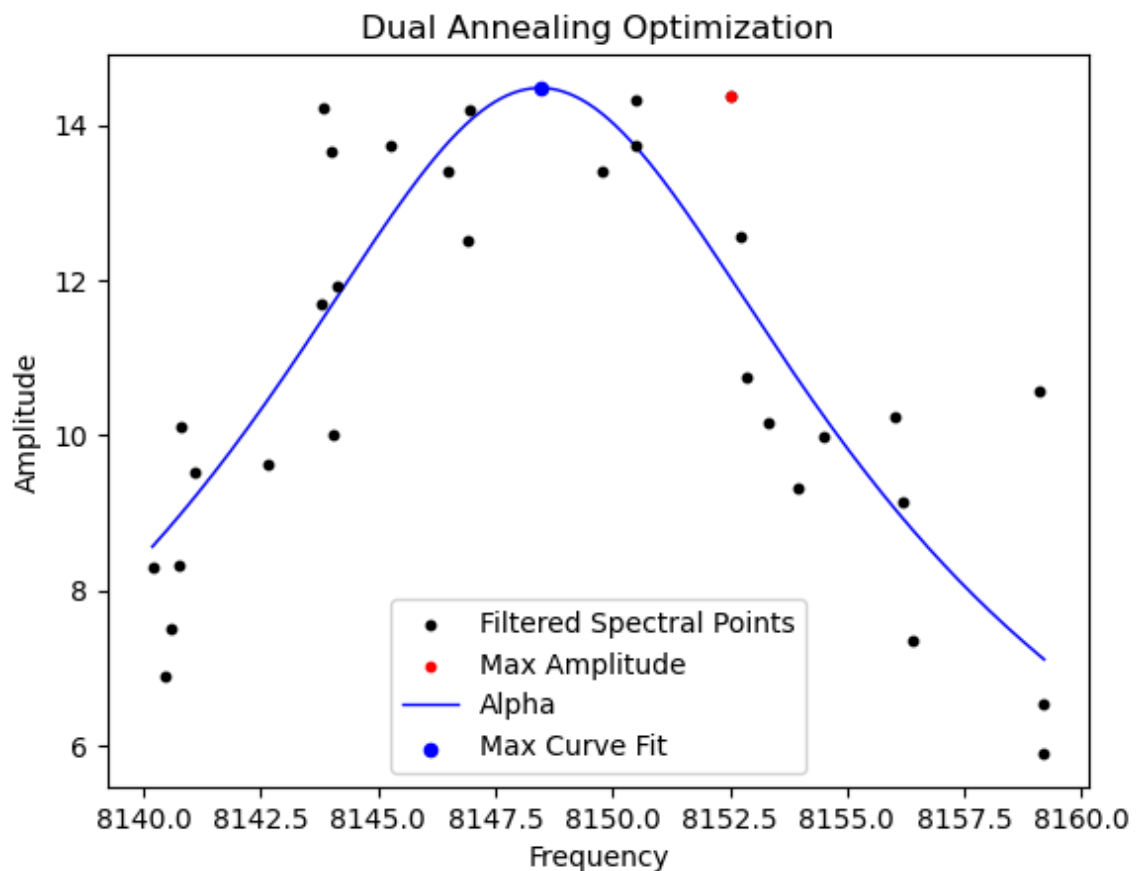
print(f"Resonant Frequency: {resonant_frequency}")
print(f"Damping Coefficient: {D}")
print(f"Force Amplitude: {F}")
print(f"Resonant Amplitude: {resonant_amplitude}")
print(f"Objective Function Value: {result.fun}")
result

```

```

/tmp/ipykernel_975535/2542982551.py:6: RuntimeWarning: invalid value encountered in divide
  V = F / (np.sqrt((1 - nue**2) ** 2 + (4 * D**2 * nue**2)))
/tmp/ipykernel_975535/2542982551.py:6: RuntimeWarning: divide by zero encountered in divide
  V = F / (np.sqrt((1 - nue**2) ** 2 + (4 * D**2 * nue**2)))
/global/mambaforge/envs/py311-pyspotseven/lib/python3.11/site-packages/scipy/optimize/_numdiff.py:590: RuntimeWarning: invalid value encountered in subtract
  df = fun(x) - f0

```



Optimized Parameters:

```

Resonant Frequency: 8148.45804766124
Damping Coefficient: 0.0007434644794704813
Force Amplitude: 0.02152990400035095
Resonant Amplitude: 14.479437222571885
Objective Function Value: 53.54144153462606

```

```

Out[153]: message: ['Maximum number of iteration reached']
          success: True
          status: 0
           fun: 53.54144153462606
            x: [ 8.148e+03  7.434e-04  2.153e-02]
           nit: 1000
          nfev: 6437
          njev: 109
          nhev: 0

```

Using Differential Evolution

```
In [154... result = differential_evolution(
    objective_function,
    bounds=bounds, # Define bounds for each parameter
    args=(J, N),
    maxiter=1000, # Maximum number of iterations
    seed=123, # Seed for reproducibility
)

# Plotting
plt.scatter(
    df1["J"],
    df1["N"],
    color="black",
    label="Filtered Spectral point",
    zorder=5,
    s=10,
)

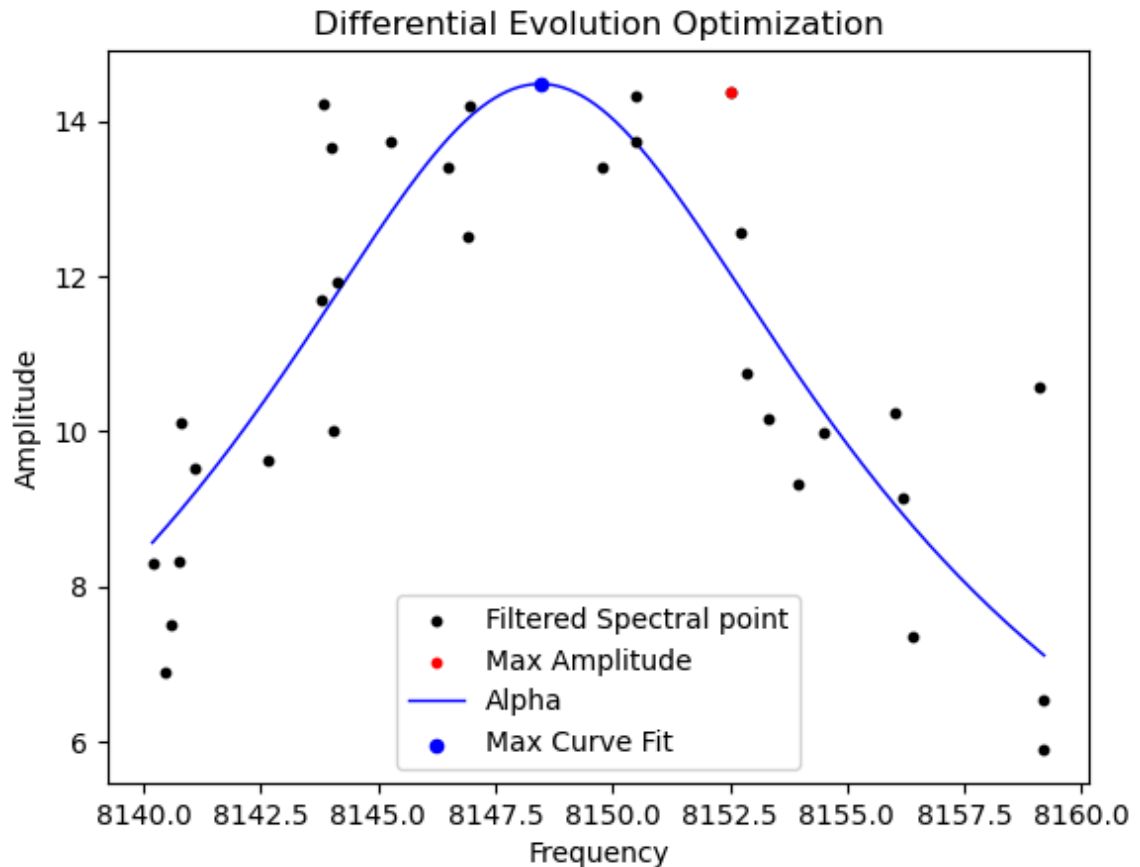
# color the max amplitude point red
plt.scatter(
    initial_0eig,
    max_N,
    color="red",
    label="Max Amplitude",
    zorder=5,
    s=10,
)

plt.plot(
    X_pred,
    ypred_one_mass_oscillator,
    label="Alpha",
    color="blue",
    linewidth=1,
)

plt.scatter(
    resonant_frequency,
    resonant_amplitude,
    color="blue",
    label="Max Curve Fit",
    zorder=10,
    s=20,
)

plt.legend()
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.title("Differential Evolution Optimization")
plt.show()

print("Optimized Parameters:")
print(f"Resonant Frequency: {resonant_frequency}")
print(f"Damping Coefficient: {D}")
print(f"Force Amplitude: {F}")
print(f"Resonant Amplitude: {resonant_amplitude}")
print(f"Objective Function Value: {result.fun}")
result
```



Optimized Parameters:

Resonant Frequency: 8148.45804766124

Damping Coefficient: 0.0007434644794704813

Force Amplitude: 0.02152990400035095

Resonant Amplitude: 14.479437222571885

Objective Function Value: 53.56531877262423

```
Out[154]: message: Optimization terminated successfully.
success: True
fun: 53.56531877262423
x: [ 8.148e+03  7.435e-04  2.153e-02]
nit: 43
nfev: 2012
population: [[ 8.148e+03  7.456e-04  2.155e-02]
             [ 8.148e+03  7.444e-04  2.149e-02]
             ...
             [ 8.148e+03  7.573e-04  2.184e-02]
             [ 8.148e+03  7.644e-04  2.199e-02]]
population_energies: [ 5.357e+01  5.371e+01 ... 5.377e+01  5.373e+01]
jac: [-1.305e+00  6.588e-01  1.656e+00]
```

Using Local Optimizers

Using Conjugate Gradient

```
In [155... result = minimize(
    objective_function,
    initial_values,
    args=(J, N),
    method='powell',
    options=options,
    bounds=bounds)
# Plotting
```



```

plt.scatter(
    df1["J"],
    df1["N"],
    color="black",
    label="Spektralkpunkte filtered",
    zorder=5,
    s=10,
)
# color the max amplitude point red
plt.scatter(
    initial_0eig,
    max_N,
    color="red",
    label="Max Amplitude",
    zorder=5,
    s=10,
)

plt.plot(
    X_pred,
    ypred_one_mass_oscillator,
    label="Alpha",
    color="blue",
    linewidth=1,
)
plt.scatter(
    resonant_frequency,
    resonant_amplitude,
    color="blue",
    label="Max Curve Fit",
    zorder=10,
    s=20,
)

plt.legend()
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.title("Powell Optimization")
plt.show()

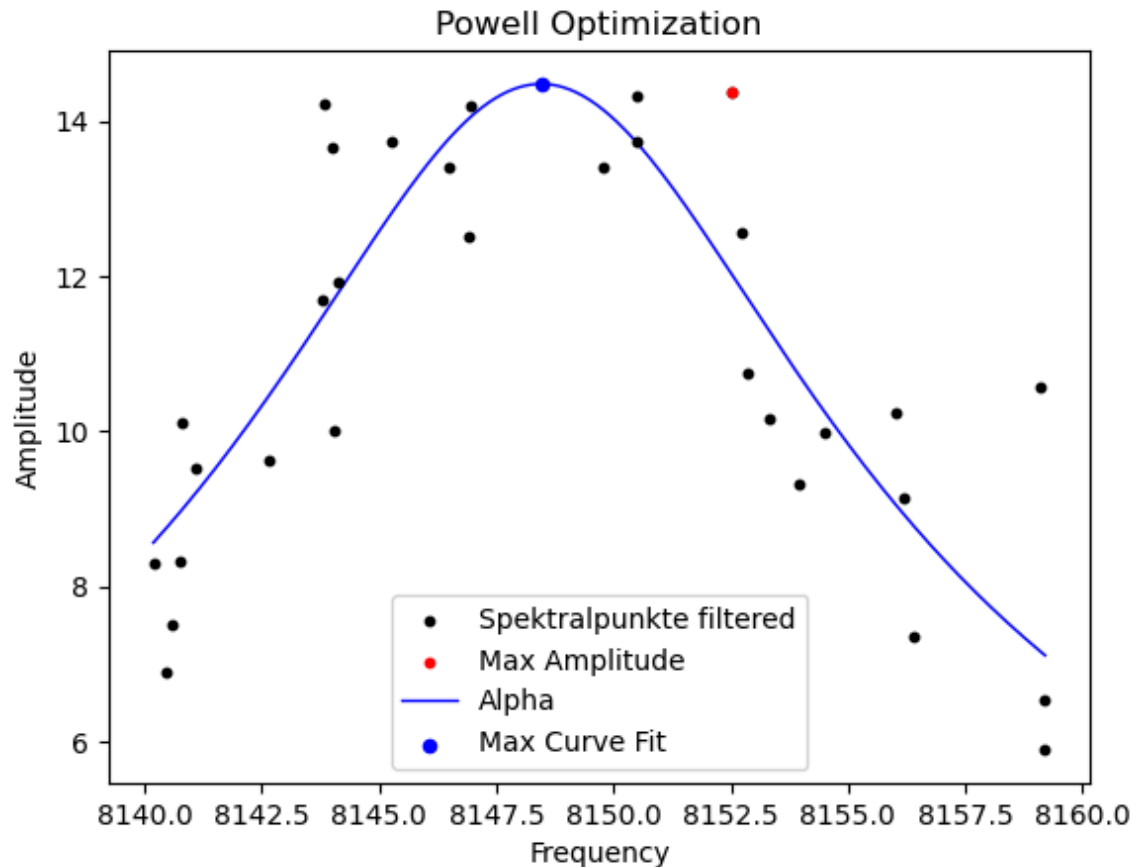
print("Optimized Parameters:")
print(f"Resonant Frequency: {resonant_frequency}")
print(f"Damping Coefficient: {D}")
print(f"Force Amplitude: {F}")
print(f"Resonant Amplitude: {resonant_amplitude}")
print(f"Objective Function Value: {result.fun}")
result

```

```

/tmp/ipykernel_975535/2450881691.py:1: OptimizeWarning: Unknown solver options: maxfun, stepmx, eta, gtol
result = minimize(

```



Optimized Parameters:

Resonant Frequency: 8148.45804766124

Damping Coefficient: 0.0007434644794704813

Force Amplitude: 0.02152990400035095

Resonant Amplitude: 14.479437222571885

Objective Function Value: 53.54144059016111

```
Out[155]: message: Optimization terminated successfully.
          success: True
          status: 0
          fun: 53.54144059016111
          x: [ 8.148e+03  7.435e-04  2.153e-02]
          nit: 11
          direc: [[ 1.978e+00 -1.935e-03 -3.893e-02]
                  [-1.091e+00 -1.473e-05 -1.175e-04]
                  [ 5.034e-08  6.736e-10 -1.229e-08]]
          nfev: 693
```

Using BFGS

```
In [157... result = minimize(
    objective_function,
    initial_values,
    args=(J, N),
    method='L-BFGS-B',
    bounds=bounds,
    options=options)
result
# Plotting
plt.scatter(
    df1["J"],
    df1["N"],
    color="black",
```

```

        label="Spektralpunkte filtered",
        zorder=5,
        s=10,
    )
    # color the max amplitude point red
    plt.scatter(
        initial_0eig,
        max_N,
        color="red",
        label="Max Amplitude",
        zorder=5,
        s=10,
    )

    plt.plot(
        X_pred,
        ypred_one_mass_oscillator,
        label="Alpha",
        color="blue",
        linewidth=1,
    )
    plt.scatter(
        resonant_frequency,
        resonant_amplitude,
        color="blue",
        label="Max Curve Fit",
        zorder=10,
        s=20,
    )

    plt.legend()
    plt.xlabel("Frequency")
    plt.ylabel("Amplitude")
    plt.title("BFGS Optimization")
    plt.show()

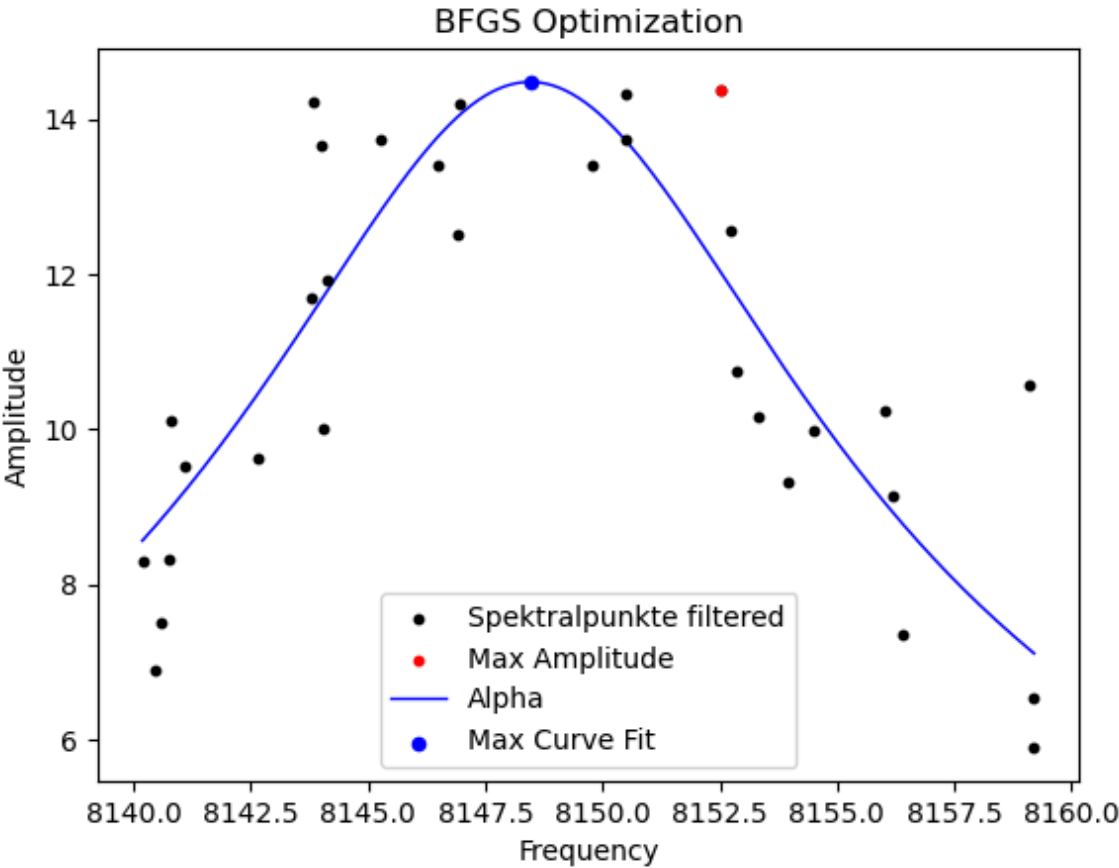
    print("Optimized Parameters:")
    print(f"Resonant Frequency: {resonant_frequency}")
    print(f"Damping Coefficient: {D}")
    print(f"Force Amplitude: {F}")
    print(f"Resonant Amplitude: {resonant_amplitude}")
    print(f"Objective Function Value: {result.fun}")
    result

```

```

/tmp/ipykernel_975535/996043608.py:1: OptimizeWarning: Unknown solver options: xtol, stepmx, eta
    result = minimize(

```



Optimized Parameters:
Resonant Frequency: 8148.45804766124
Damping Coefficient: 0.0007434644794704813
Force Amplitude: 0.02152990400035095
Resonant Amplitude: 14.479437222571885
Objective Function Value: 53.54144117175894

```
Out[157]: message: CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
success: True
status: 0
fun: 53.54144117175894
x: [ 8.148e+03  7.434e-04  2.153e-02]
nit: 28
jac: [ 1.419e-03  1.073e+01 -1.476e-01]
nfev: 188
njev: 47
hess_inv: <3x3 LbfgsInvHessProduct with dtype=float64>
```

Comparision of different Optimisers

Optimizer	Scope(local/Global optimizer)	Objective Function Value	Number of Evaluations	Number of Iterations	Observations
Dual Annealing	Global	53.54144153462606	6437	1000	Achieved global optimum with the minimum function evaluation
Differential Evolution	Global	53.54938461678095	2012	43	Finds optimum solution with fewer evaluations

Optimizer	Scope(local/Global optimizer)	Objective Function Value	Number of Evaluations	Number of Iterations	Observations
					evaluated more than 1000 iterations, but it didn't find the absolute best solution.
Powell's	Local	53.54144059016111	693	11	Powell's method is efficient and finds a good local optimum solution with a lower number of iterations compared to Dual Annealing, but it doesn't guarantee finding the absolute best solution.
Nelder-Mead	local	53.54144061205875	169	93	Efficient and finds a good local optimum solution with fewer iterations.
L-BFGS-B	local	53.54144117175894	188	28	Quickly converges to a local optimum, but the least number of iterations is not the only factor to consider.

Conclusion

The table highlights the trade-off between finding the absolute best solution (global optimum) and the computational cost of the optimization algorithm. Methods that guarantee the global optimum require significant processing power, while faster approaches might settle for very good solutions that aren't necessarily the absolute best. The optimal choice depends on the specific problem and the importance placed on finding the absolute best solution versus efficiency.

Optimization of 2nd Data Frame

Using Global Optimizers

In [158...

```
df1 = pd.read_pickle("df1.pkl")
df2 = pd.read_pickle("df2.pkl")
# Printing the lengths of the DataFrames
print("Length of df1:", len(df1))
```

```
print("Length of df2:", len(df2))
```

```
Length of df1: 33
Length of df2: 66
```

```
In [159... threshold = 0.4
df2.sort_values("N")
max_N = max(df2["N"])
df2 = df2[df2["N"]>=threshold*max_N]
len(df2)
```

```
Out[159]: 23
```

We extract the frequency value for maximum value of the amplitude. This serves as the initial value for one decision variable.

```
In [160... df_max=df2[df2["N"]==max(df2["N"])]
initial_0eig = df_max["J"].values[0]
max_N = df_max["N"].values[0]
```

We also have to define the other two initial guesses

```
In [161... initial_D = 0.006
initial_F = 0.120

initial_values = [initial_0eig, initial_D, initial_F]
```

Additionally we define the bounds for the decision variables

```
In [162... min_0err = min(df2["J"])
max_0err = max(df2["J"])

In [163... bounds = [(min_0err, max_0err), (0, 0.03), (0, 1)]
```

Then we define the objective function

```
In [164... def one_mass_oscillator(params, 0err) -> np.ndarray:
    # returns amplitudes of the system
    # Defines the model of a one mass oscillator
    0eig, D, F = params
    nue = 0err / 0eig
    V = F / (np.sqrt((1 - nue**2) ** 2 + (4 * D**2 * nue**2)))
    return V

In [165... def objective_function(params, 0err, amplitudes) -> np.ndarray:
    # objective function to compare calculated and real amplitudes
    return np.sum((amplitudes - one_mass_oscillator(params, 0err)) ** 2)
```

We define the options and start the optimization process

```
In [166... options = {
    "maxfun": 100000,
    "ftol": 1e-9,
    "xtol": 1e-9,
```

```

    "stepmx": 10,
    "eta": 0.25,
    "gtol": 1e-5}
J = np.array(df2["J"]) # measured frequency
N = np.array(df2["N"]) # measured amplitude

```

```

In [167... result = minimize(
    objective_function,
    initial_values,
    args=(J, N),
    method='Nelder-Mead',
    bounds=bounds,
    options=options)

```

```

/tmp/ipykernel_975535/2959858538.py:1: OptimizeWarning: Unknown solver options: maxfun, ftol, xtol, stepmx, eta, gtol
result = minimize(

```

```

In [168... # map optimized values to variables
resonant_frequency = result.x[0]
D = result.x[1]
F = result.x[2]
# predict the resonant amplitude with the fitted one mass oscillator.
X_pred = np.linspace(min_0err, max_0err, 1000)
ypred_one_mass_oscillator = one_mass_oscillator(result.x, X_pred)
resonant_amplitude = max(ypred_one_mass_oscillator)
result

```

```

Out[168]:      message: Optimization terminated successfully.
      success: True
      status: 0
      fun: 229.4092648339145
      x: [ 8.147e+03  1.099e-03  7.021e-02]
      nit: 135
      nfev: 239
      final_simplex: (array([[ 8.147e+03,  1.099e-03,  7.021e-02],
                             [ 8.147e+03,  1.099e-03,  7.021e-02],
                             [ 8.147e+03,  1.099e-03,  7.021e-02],
                             [ 8.147e+03,  1.099e-03,  7.021e-02]]), array([
2.294e+02,  2.294e+02,  2.294e+02,  2.294e+02]))

```

Using Dual Annealing

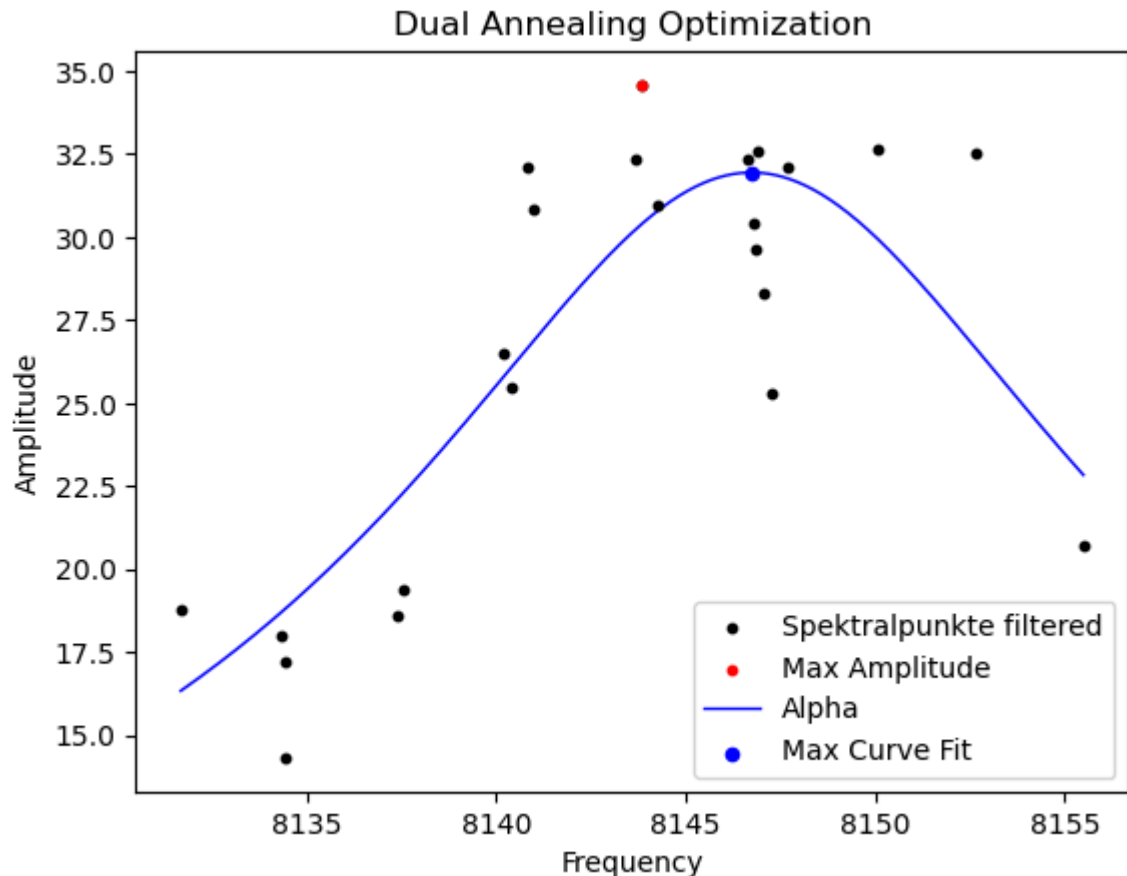
```

In [169... result = dual_annealing(
    objective_function,
    bounds=bounds,
    args=(J, N),
    maxiter=1000, # Maximum number of iterations
    seed=123, # Seed for reproducibility
)

# Plotting
plt.scatter(
    df2["J"],
    df2["N"],
    color="black",
    label="Spektralkpunkte filtered",
    zorder=5,
    s=10,

```

```
)  
# color the max amplitude point red  
plt.scatter(  
    initial_0eig,  
    max_N,  
    color="red",  
    label="Max Amplitude",  
    zorder=5,  
    s=10,  
)  
  
plt.plot(  
    X_pred,  
    ypred_one_mass_oscillator,  
    label="Alpha",  
    color="blue",  
    linewidth=1,  
)  
plt.scatter(  
    resonant_frequency,  
    resonant_amplitude,  
    color="blue",  
    label="Max Curve Fit",  
    zorder=10,  
    s=20,  
)  
  
plt.legend()  
plt.xlabel("Frequency")  
plt.ylabel("Amplitude")  
plt.title("Dual Annealing Optimization")  
plt.show()  
  
print("Optimized Parameters:")  
print(f"Resonant Frequency: {resonant_frequency}")  
print(f"Damping Coefficient: {D}")  
print(f"Force Amplitude: {F}")  
print(f"Resonant Amplitude: {resonant_amplitude}")  
print(f"Objective Function Value: {result.fun}")  
result
```

Optimized Parameters:

Resonant Frequency: 8146.746051852071

Damping Coefficient: 0.0010989248372497854

Force Amplitude: 0.07020956698446057

Resonant Amplitude: 31.94467402394625

Objective Function Value: 229.4092694161751

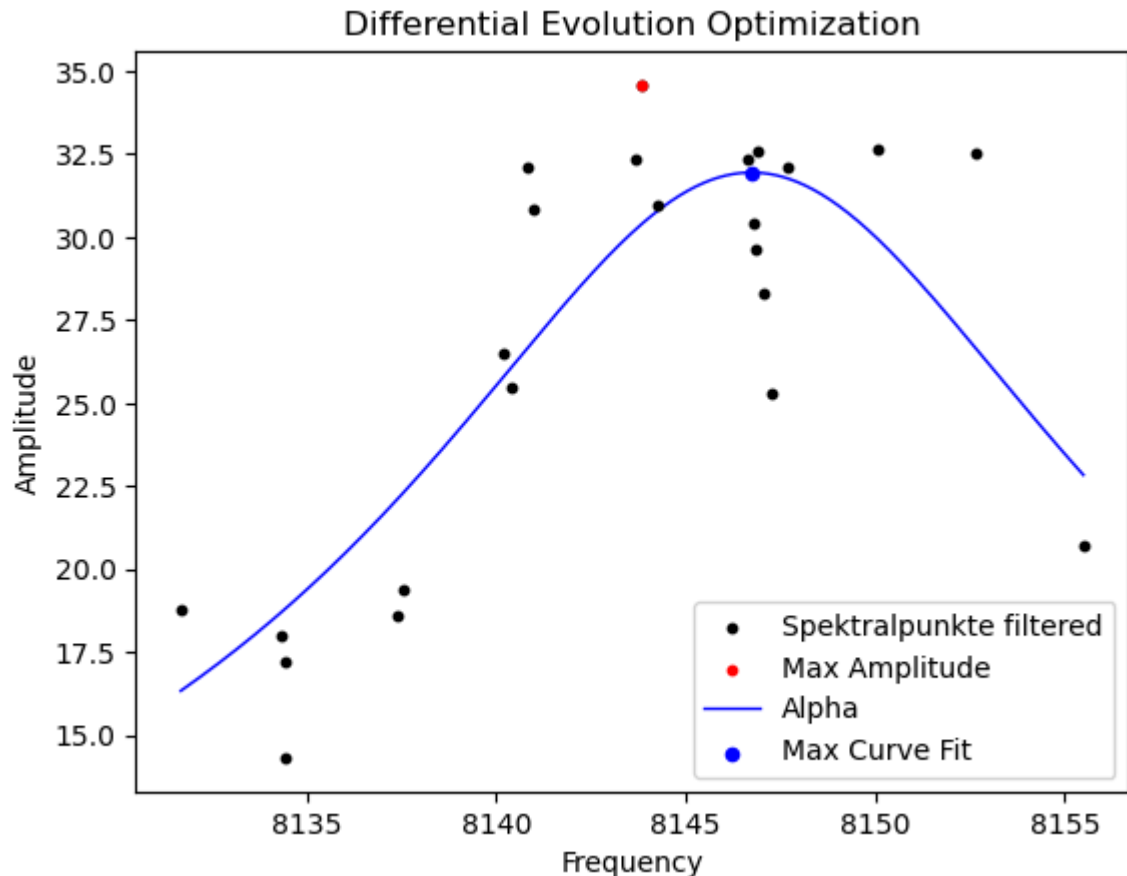
```
Out[169]: message: ['Maximum number of iteration reached']
          success: True
          status: 0
          fun: 229.4092694161751
             x: [ 8.147e+03  1.099e-03  7.020e-02]
          nit: 1000
          nfev: 6181
          njev: 45
          nhev: 0
```

Using Differential Evolution

```
In [170... result = differential_evolution(
    objective_function,
    bounds=bounds, # Define bounds for each parameter
    args=(J, N),
    maxiter=1000, # Maximum number of iterations
    seed=123, # Seed for reproducibility
)

# Plotting
plt.scatter(
    df2["J"],
    df2["N"],
    color="black",
    label="Spektralpunkte filtered",
```

```
        zorder=5,  
        s=10,  
    )  
    # color the max amplitude point red  
    plt.scatter(  
        initial_Oeig,  
        max_N,  
        color="red",  
        label="Max Amplitude",  
        zorder=5,  
        s=10,  
    )  
  
    plt.plot(  
        X_pred,  
        ypred_one_mass_oscillator,  
        label="Alpha",  
        color="blue",  
        linewidth=1,  
    )  
    plt.scatter(  
        resonant_frequency,  
        resonant_amplitude,  
        color="blue",  
        label="Max Curve Fit",  
        zorder=10,  
        s=20,  
    )  
  
    plt.legend()  
    plt.xlabel("Frequency")  
    plt.ylabel("Amplitude")  
    plt.title("Differential Evolution Optimization")  
    plt.show()  
  
    print("Optimized Parameters:")  
    print(f"Resonant Frequency: {resonant_frequency}")  
    print(f"Damping Coefficient: {D}")  
    print(f"Force Amplitude: {F}")  
    print(f"Resonant Amplitude: {resonant_amplitude}")  
    print(f"Objective Function Value: {result.fun}")  
    result
```



Optimized Parameters:
 Resonant Frequency: 8146.746051852071
 Damping Coefficient: 0.0010989248372497854
 Force Amplitude: 0.07020956698446057
 Resonant Amplitude: 31.94467402394625
 Objective Function Value: 229.4192718479083

```
Out[170]:      message: Optimization terminated successfully.
      success: True
      fun: 229.4192718479083
      x: [ 8.147e+03  1.101e-03  7.035e-02]
      nit: 37
      nfev: 1778
      population: [[ 8.147e+03  1.102e-03  7.043e-02]
                   [ 8.147e+03  1.109e-03  7.042e-02]
                   ...
                   [ 8.147e+03  1.178e-03  7.560e-02]
                   [ 8.147e+03  1.097e-03  7.063e-02]]
      population_energies: [ 2.294e+02  2.299e+02 ... 2.351e+02  2.303e+02]
      jac: [ 7.201e-01 -1.267e+00 -4.011e+00]
```

Using Local Optimizers

Using Conjugate Gradient

```
In [171]: result = minimize(
    objective_function,
    initial_values,
    args=(J, N),
    method='powell',
    options=options,
    bounds=bounds)
```

```

# Plotting
plt.scatter(
    df2["J"],
    df2["N"],
    color="black",
    label="Spektralkpunkte filtered",
    zorder=5,
    s=10,
)
# color the max amplitude point red
plt.scatter(
    initial_0eig,
    max_N,
    color="red",
    label="Max Amplitude",
    zorder=5,
    s=10,
)

plt.plot(
    X_pred,
    ypred_one_mass_oscillator,
    label="Alpha",
    color="blue",
    linewidth=1,
)
plt.scatter(
    resonant_frequency,
    resonant_amplitude,
    color="blue",
    label="Max Curve Fit",
    zorder=10,
    s=20,
)

plt.legend()
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.title("Powell Optimization")
plt.show()

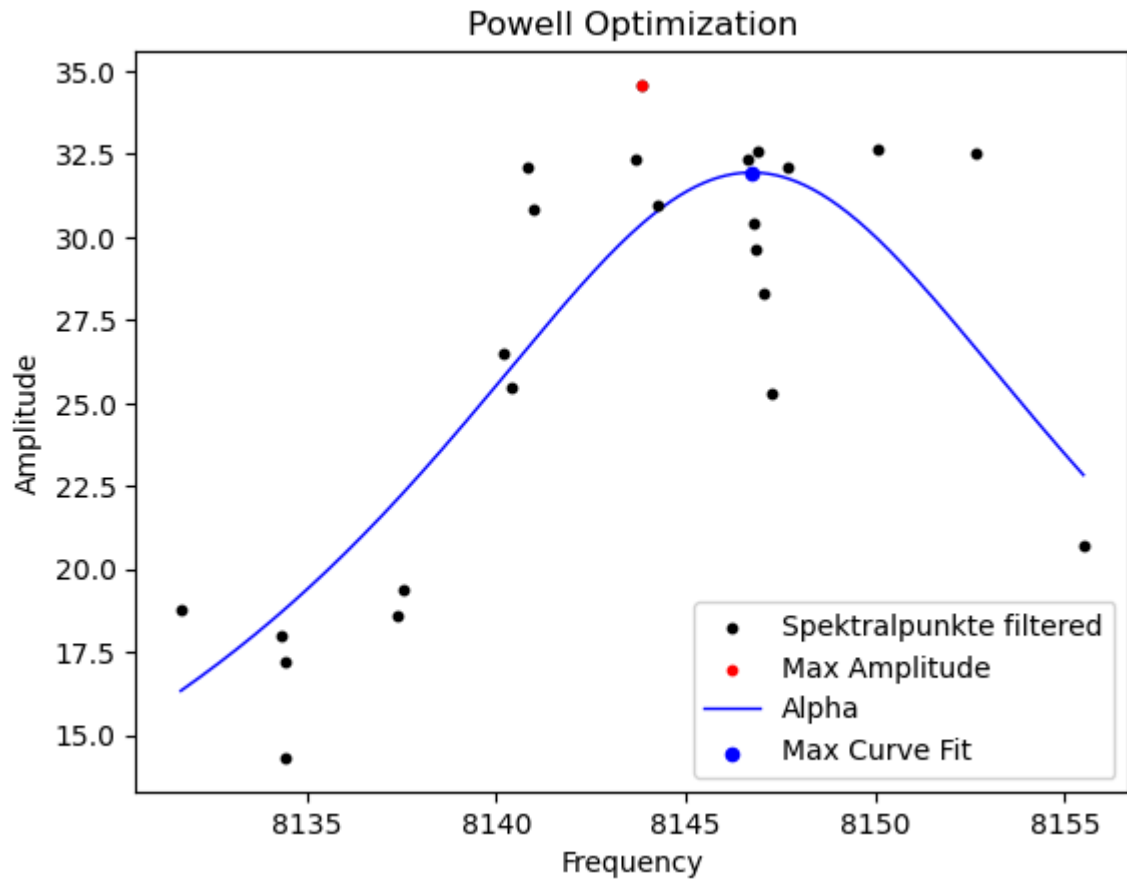
print("Optimized Parameters:")
print(f"Resonant Frequency: {resonant_frequency}")
print(f"Damping Coefficient: {D}")
print(f"Force Amplitude: {F}")
print(f"Resonant Amplitude: {resonant_amplitude}")
print(f"Objective Function Value: {result.fun}")
result

```

```

/tmp/ipykernel_975535/110192510.py:1: OptimizeWarning: Unknown solver options: maxfun, stepmx, eta, gtol
result = minimize(

```



Optimized Parameters:

Resonant Frequency: 8146.746051852071

Damping Coefficient: 0.0010989248372497854

Force Amplitude: 0.07020956698446057

Resonant Amplitude: 31.94467402394625

Objective Function Value: 229.4092648056204

```
Out[171]: message: Optimization terminated successfully.
          success: True
          status: 0
          fun: 229.4092648056204
             x: [ 8.147e+03  1.099e-03  7.021e-02]
          nit: 9
         direc: [[-2.151e+00 -5.559e-04 -2.909e-02]
                  [ 1.226e+00 -3.584e-05 -5.327e-04]
                  [-1.653e-02 -2.415e-06 -2.265e-04]]
          nfev: 586
```

Using BFGS

```
In [172... result = minimize(
    objective_function,
    initial_values,
    args=(J, N),
    bounds=bounds,
    options=options)
result
# Plotting
plt.scatter(
    df2["J"],
    df2["N"],
    color="black",
    label="Spektralpunkte filtered",
```

```

        zorder=5,
        s=10,
    )
    # color the max amplitude point red
    plt.scatter(
        initial_0eig,
        max_N,
        color="red",
        label="Max Amplitude",
        zorder=5,
        s=10,
    )

    plt.plot(
        X_pred,
        ypred_one_mass_oscillator,
        label="Alpha",
        color="blue",
        linewidth=1,
    )
    plt.scatter(
        resonant_frequency,
        resonant_amplitude,
        color="blue",
        label="Max Curve Fit",
        zorder=10,
        s=20,
    )

    plt.legend()
    plt.xlabel("Frequency")
    plt.ylabel("Amplitude")
    plt.title("BFGS Optimization")
    plt.show()

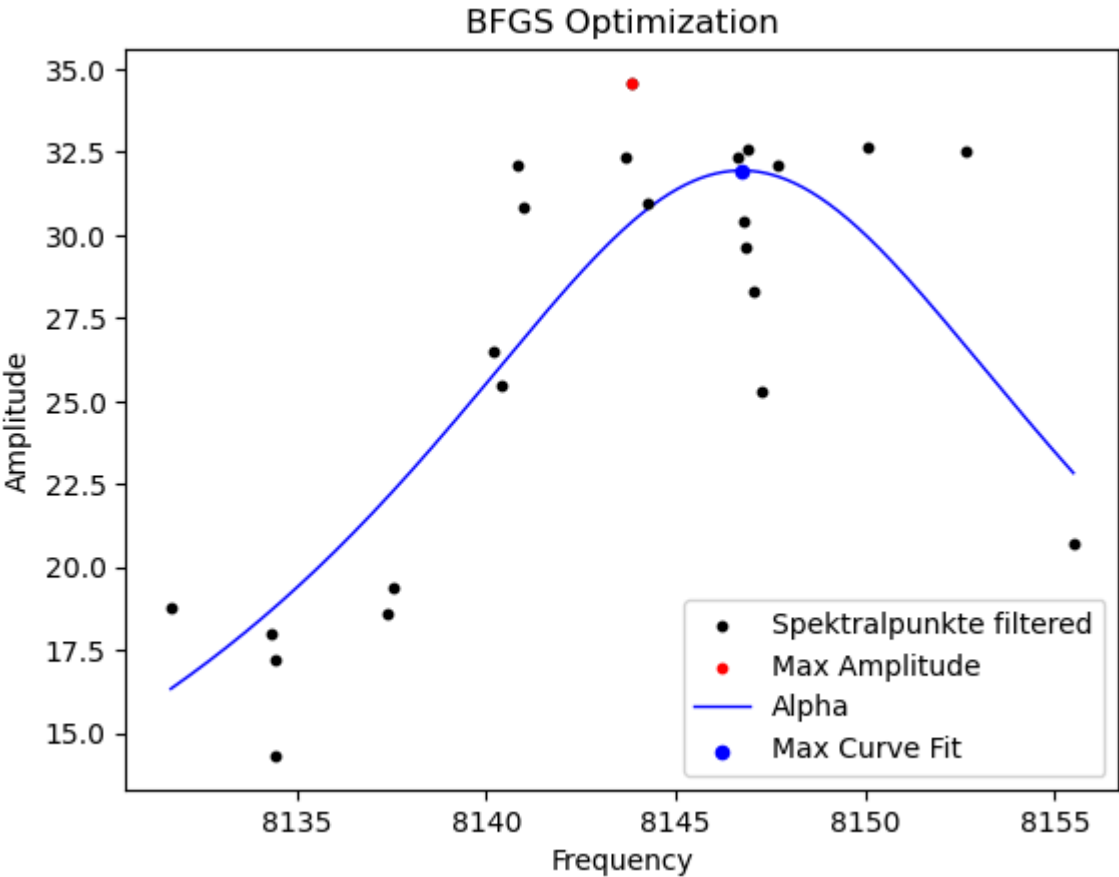
    print("Optimized Parameters:")
    print(f"Resonant Frequency: {resonant_frequency}")
    print(f"Damping Coefficient: {D}")
    print(f"Force Amplitude: {F}")
    print(f"Resonant Amplitude: {resonant_amplitude}")
    print(f"Objective Function Value: {result.fun}")
    result

```

```

/tmp/ipykernel_975535/2860355532.py:1: OptimizeWarning: Unknown solver options: xtol, stepmx, eta
result = minimize(

```



Optimized Parameters:
Resonant Frequency: 8146.746051852071
Damping Coefficient: 0.0010989248372497854
Force Amplitude: 0.07020956698446057
Resonant Amplitude: 31.94467402394625
Objective Function Value: 229.4092692624839

```
Out[172]: message: CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
success: True
status: 0
fun: 229.4092692624839
x: [ 8.147e+03  1.099e-03  7.020e-02]
nit: 20
jac: [ 1.154e-03  8.419e+00 -1.765e-01]
nfev: 180
njev: 45
hess_inv: <3x3 LbfgsInvHessProduct with dtype=float64>
```

Comparison of different Optimisers

Optimizer	Scope(local/Global optimizer)	Objective Function Value	Number of Evaluations	Number of Iterations	Observations
Dual Annealing	Global	229.4092694161751	6181	1000	Finds optimum solution with the highest number of evaluations and iterations
DifferentialEvolution	Global	229.4192718479083	1778	37	Achieved near-optimal solution

Optimizer	Scope(local/Global optimizer)	Objective Function Value	Number of Evaluations	Number of Iterations	Observations
					solution found, fewer evaluations and iterations compared to dual annealing.
Nelder-Mead	Local	229.4092648339145	239	135	Efficient convergence to a near-optimal solution with minimal evaluations and iterations.
Powell's	local	229.4092648056204	586	9	Powell's method is efficient for finding local optima, requiring fewer evaluations than Dual Annealing but it may not find the absolute solution.
L-BFGS-B	local	229.4092692624839	180	45	Quickly reaches a local optimum solution with fewer evaluations and a moderate number of iterations.

Conclusion

Based on the table, there's a trade-off between finding the absolute best solution (global optimum) and the efficiency of the optimization algorithm. Algorithms that guarantee a global optimum (like Dual Annealing) require more evaluations and iterations. Conversely, faster algorithms (like Nelder-Mead or Powell's method) might converge to very good solutions (local optima) but potentially miss the absolute best.