Dynamical Systems Homework 1

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```
[1]: # toc (adds a table of contents)
     from typing import Callable, List, Iterable

     import matplotlib.pyplot as plt
     import numpy as np
     import sympy as sp
     from scipy.integrate import odeint
     from scipy.interpolate import interp1d
     import pandas as pd

     plt.style.use('../maroon_ipynb.mplstyle')  # applies MSU theme to plots
```

Contents

Problem 1

Given

$$\frac{d^2x}{dt^2} - \mu\left(1 - x^2\right)\frac{dx}{dt} + x - A\sin(\omega t) = 0$$

where $\mu = 1$, $\omega = \frac{2\pi}{10}$, and $A = 10$

Find

From the differential equation above,

a. Find the state variable form.
b. Use Euler's Explicit method to obtain a numerical solution of the state variable equations from part (a). Assume zero initial conditions and that $t \leq 20$. Find the smallest value of Δt that gives a converged solution (solution doesn't change as time step decreases).
c. Repeat part (b) using a fourth order runge kutta solver with a fixed time step.
d. The results in parts (b) and (c) should be the same, but the value of Δt chosen for (c) should be smaller than that for part (b). If the method used in part (c) requires four times the computational resources per time step, compare the computational resources for each case.

Solution

Part A

```
[2]: mu_, omega_, A_ = 1, 2*np.pi/10, 10   # constants (units not given)

     # Defining the ODE
     t, mu, omega, A = sp.symbols('t mu omega A')
     x0 = sp.Function('x_0')(t)

     eq = sp.Eq(x0.diff(t, 2) - mu*(1 - x0**2)*x0.diff(t) + x0 - A*sp.sin(omega*t), ↵
     ↳0)
     eq
```

[2]:
$$-A\sin\left(\omega t\right) - \mu\left(1 - x_0^2(t)\right)\frac{d}{dt}x_0(t) + x_0(t) + \frac{d^2}{dt^2}x_0(t) = 0$$

This is a just a single second order ODE, so it only requires one state variable to make a system of first order ODEs.

```
[3]: # Define the new state variable
     x1 = sp.Function('x_1')(t)

     # Add the new state variable as the second equation
     eq2 = sp.Eq(x1, x0.diff(t))

     # Substitute the second state variable into the original equation
     eq1 = eq.subs(x0.diff(t), x1)
     display(eq1, eq2)
```

3

$$-A\sin\left(\omega t\right) - \mu\left(1 - x_0^2(t)\right)x_1(t) + x_0(t) + \frac{d}{dt}x_1(t) = 0$$

$$x_1(t) = \frac{d}{dt}x_0(t)$$

```
[4]: # Solve the system of equations
     sol = sp.solve([eq1, eq2], [x0.diff(), x1.diff()], dict=True)[0]
     for key, value in sol.items():
         display(sp.Eq(key, value))
```

$$\frac{d}{dt}x_0(t) = x_1(t)$$

$$\frac{d}{dt}x_1(t) = A\sin\left(\omega t\right) - \mu x_0^2(t)x_1(t) + \mu x_1(t) - x_0(t)$$

As seen above, only first order derivatives are on the left hand side. This is the state variable form, but we can just manually write the python function for numerical use with how simple this is. For more complex problems, you can automate the conversion from `sympy` operations to python or `numpy` operations by using the `lambdify` function.

```
[5]: # Defining state variable function
     def state_vars(x, t_):
         return [
             x[1],
             A_*np.sin(omega_*t_) - mu_*x[0]**2*x[1] + mu_*x[1] - x[0]
         ]
```

Part B

The below code cell is the routine for Euler's Explicit method and takes into account any number of ODE's.

```
[6]: def euler_explicit(func: Callable, y0: List | Iterable, t_values: List |␣
     ↪Iterable) -> List:
         n = len(func(y0, t_values[0]))
         arrays = [[y0_] for y0_ in y0]

         for i in range(len(t_values) - 1):
             h = t_values[i + 1] - t_values[i]
             current_state = [array[-1] for array in arrays]
             derivatives = func(current_state, t_values[i])
             for j in range(n):
                 arrays[j].append(arrays[j][-1] + h*derivatives[j])

         return arrays
```

To measure the error of the Euler's Explicit method, we can compare it to the `scipy` solution using the `odeint` function. We can assume that the `scipy` solution is the true solution and the error will be determined by

4

$$err = max(|x_num - x_exact|)$$

We will choose the time step that gives $err < 10^{-3}$.

```python
err = 1
del_t = 0.1
t_array, x0_euler, x1_euler, scipy_sol = None, None, None, None
while err > 1e-3:
    del_t /= 2
    t_array = np.arange(0, 20, del_t)
    sol = euler_explicit(state_vars, [0, 0], t_array)
    scipy_sol = odeint(state_vars, [0, 0], t_array)
    x0_euler, x1_euler = np.array(sol[0]), np.array(sol[1])
    err = np.max(np.abs(x0_euler - scipy_sol[:, 0]))

fig, ax = plt.subplots(nrows=1, ncols=2)
ax[0].plot(t_array, x0_euler, label='Euler Explicit')
ax[0].plot(t_array, scipy_sol[:, 0], label='Scipy', ls='--')
ax[1].plot(t_array, x1_euler, label='Euler Explicit')
ax[1].plot(t_array, scipy_sol[:, 1], label='Scipy', ls='--')
ax[0].set_ylabel('$x_0(t)$')
ax[1].set_ylabel('$x_1(t)$')
ax[0].set_xlabel('Time ($s$)')
ax[1].set_xlabel('Time ($s$)')
ax[0].legend()
ax[1].legend()
plt.show()
```

```python
[8]: del_t_euler = del_t
del_t_euler # resulting time step used above
```

```
[8]: 2.44140625e-05
```

Part C

Similarly to Part B, here is the routine for the fourth order Runge-Kutta method.

```python
[9]: def runge_kutta(func: Callable, y0: List | Iterable, t_values: List | Iterable)
     ↪-> List:
    n = len(func(y0, t_values[0]))
    arrays = [[y0_] for y0_ in y0]

    for i in range(len(t_values) - 1):
        h = t_values[i + 1] - t_values[i]
        K1 = func([array[i] for array in arrays], t_values[i])
        K2 = func([array[i] + 0.5*h*K for array, K in zip(arrays, K1)],
     ↪t_values[i] + 0.5*h)
```

5

```python
        K3 = func([array[i] + 0.5*h*K for array, K in zip(arrays, K2)],
    t_values[i] + 0.5*h)
        K4 = func([array[i] + h*K for array, K in zip(arrays, K3)], t_values[i]
    + h)

        for j in range(n):
            arrays[j].append(arrays[j][i] + h/6*(K1[j] + 2*K2[j] + 2*K3[j] +
    K4[j]))

    return arrays

err = 1
del_t = 0.1
t_array, x0_rk, x1_rk = None, None, None
while err > 1e-3:
    del_t /= 2
    t_array = np.arange(0, 20, del_t)
    sol = runge_kutta(state_vars, [0, 0], t_array)
    scipy_sol = odeint(state_vars, [0, 0], t_array)
    x0_rk, x1_rk = np.array(sol[0]), np.array(sol[1])
    err = np.max(np.abs(x0_rk - scipy_sol[:, 0]))

fig, ax = plt.subplots(nrows=1, ncols=2)
ax[0].plot(t_array, x0_rk, label='Runge-Kutta')
ax[0].plot(t_array, scipy_sol[:, 0], label='Scipy', ls='--')
ax[1].plot(t_array, x1_rk, label='Runge-Kutta')
ax[1].plot(t_array, scipy_sol[:, 1], label='Scipy', ls='--')
ax[0].set_ylabel('$x_0(t)$')
ax[1].set_ylabel('$x_1(t)$')
ax[0].set_xlabel('Time ($s$)')
ax[1].set_xlabel('Time ($s$)')
ax[0].legend()
ax[1].legend()
plt.show()
```
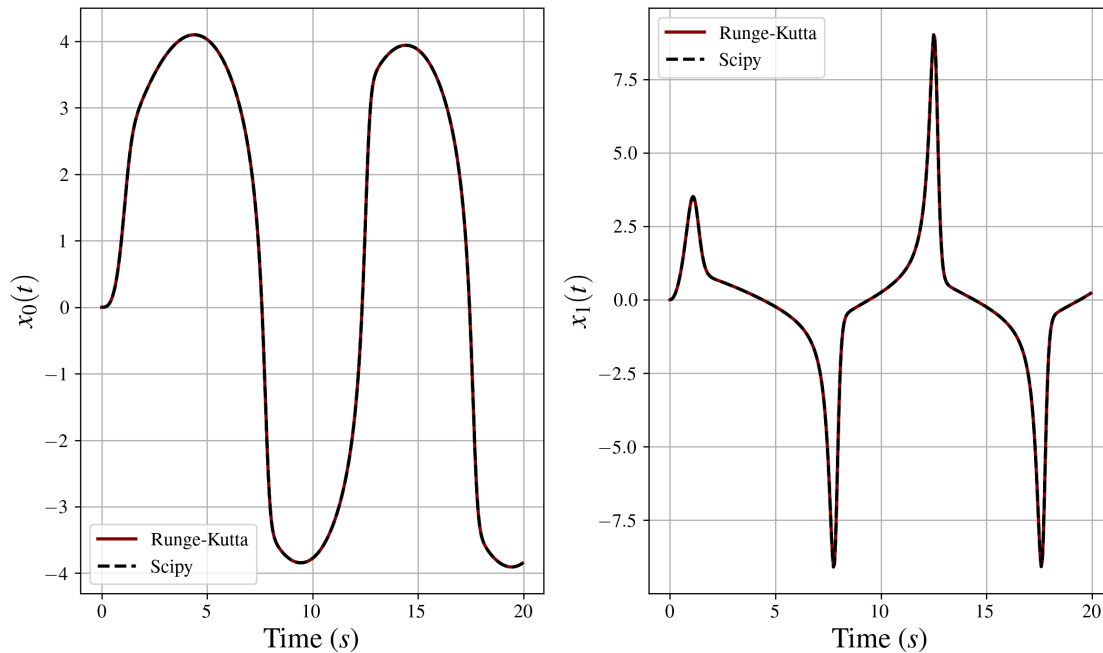
```
[10]: del_t_rk = del_t
      del_t_rk # resulting time step used above
```

```
[10]: 0.05
```

Part D

As you can see above, with the convergence criteria, the Euler Explicit method converges at a time step of $2.44140625 \cdot 10^{-5}$, and the Runge-Kutta method converges at a time step of 0.5. The Runge-Kutta method, however, has four times more computations for each time step, but has far fewer time steps to converge.

```
[11]: euler_array_size = np.arange(0, 20, del_t_euler).size
      rk_array_size = np.arange(0, 20, del_t_rk).size
      euler_array_size, rk_array_size
```

```
[11]: (819200, 400)
```

The above output shows that the Euler Explicit array has a size of 819200, while the Runge-Kutta has a size of 400. Even with the four extra computations per time step, the Runge-Kutta method is more computationally efficient because $4 \cdot 400 = 1600 << 819200$.

Verification

The above problems show that the `scipy` solver agrees with the Euler Explicit and Runge-Kutta methods. We can further verify that this solution is correct by testing the original differential equation. We can plug each solution into the original equation and see if the error is close to zero.

```
[12]: x0, x1 = scipy_sol[:, 0], scipy_sol[:, 1]
      x1_dot = np.gradient(x1, t_array, edge_order=2)
      err = x1_dot - mu_*(1 - x0**2)*x1 + x0 - A_*np.sin(omega_*t_array)
      np.mean(err)
```
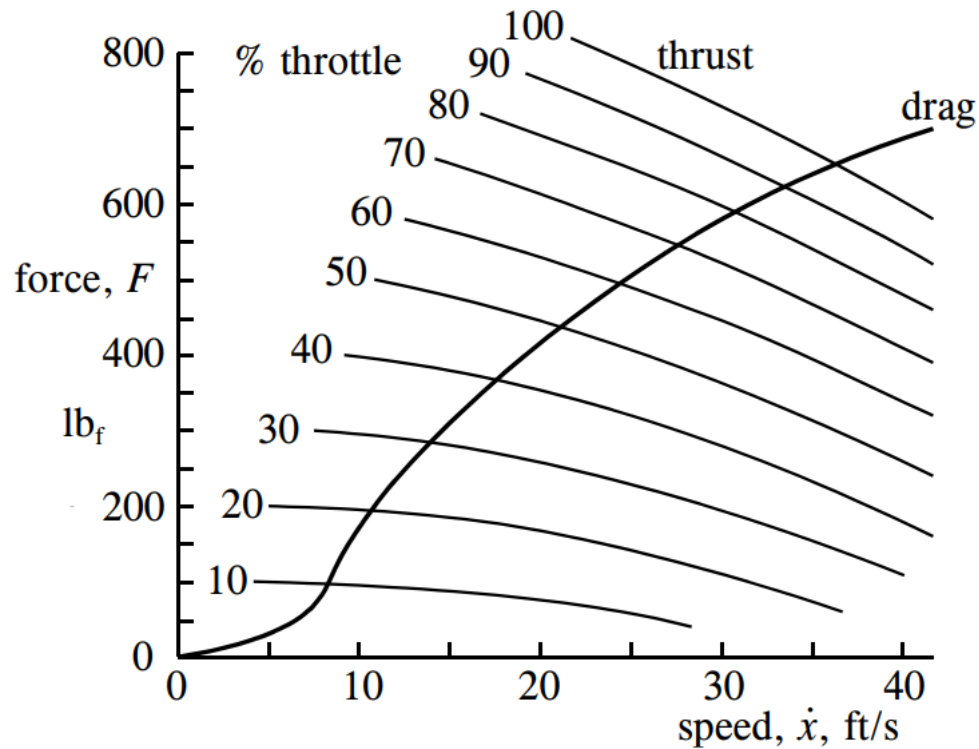
[12]: -0.0001447673813758238

The above cell finds the mean error for each time step and shows that the error is very close to zero.

Problem 2

Given

The above image shows thrust/speed and drag force on a 4000 lbs boat. The thrust is based on the throttle position indicated as a percentage. The boat is traveling at a steady 20 ft/s until the throttle abruptly resets to 80%.

Find

    a. Find the thrust and drag forces before the velocity has time to change.
    b. Find the instantaneous acceleration of the boat.

Solution

Part A

The force balance for this system is simply

$$F_{thrust} - F_{drag} = ma$$

```
[13]: m = 4000/32.174   # mass in slugs

      # Plotting the curves of interest
      drag = pd.read_csv('drag.csv')
      thrust_40 = pd.read_csv('thrust40.csv')
```

```
thrust_50 = pd.read_csv('thrust50.csv')
thrust_80 = pd.read_csv('thrust80.csv')
```

If the boat is initially travelling at a constant 20 ft/s, then the thrust and force values must be equal.

[14]:
```
# Interpolating the drag force curve and finding force at 20 ft/s
drag_force = interp1d(drag['speed'], drag['force'], kind='linear')
F_drag = np.float64(drag_force(20))
F_drag  # lbs
```

[14]: 413.98524403963677

[15]:
```
# Interpolating the thrust force curve at 80% throttle to find the thrust force␣
  ↪at 20 ft/s
thrust_force_80 = interp1d(thrust_80['speed'], thrust_80['force'],␣
  ↪kind='linear')
F_thrust = np.float64(thrust_force_80(20))
F_thrust  # lbs
```

[15]: 688.5774442946789

Part B

The instant that the throttle is changed to 80%, the force state of on the boat is $F_{thrust} - F_{drag}$, which was determined above. The acceleration is simply that divided by the mass.

[16]:
```
a = (F_thrust - F_drag)/m
a  # ft/s^2
```

[16]: 2.2086823627514316

Verification

You can see the calculated values more clearly by plotting the dataset. The graph below shows the thrust and drag forces were correctly interpolated at 20 ft/s.

[17]:
```
fig, ax = plt.subplots()
ax.plot(drag['speed'], drag['force'], label='Drag Force')
ax.plot(thrust_40['speed'], thrust_40['force'], label=r'Thrust Force (40\%)')
ax.plot(thrust_50['speed'], thrust_50['force'], label=r'Thrust Force (50\%)')
ax.plot(thrust_80['speed'], thrust_80['force'], label=r'Thrust Force (80\%)')
ax.set_xlabel('Speed ($ft/s$)')
ax.set_ylabel('Force ($lbs$)')
ax.legend()
plt.show()
```
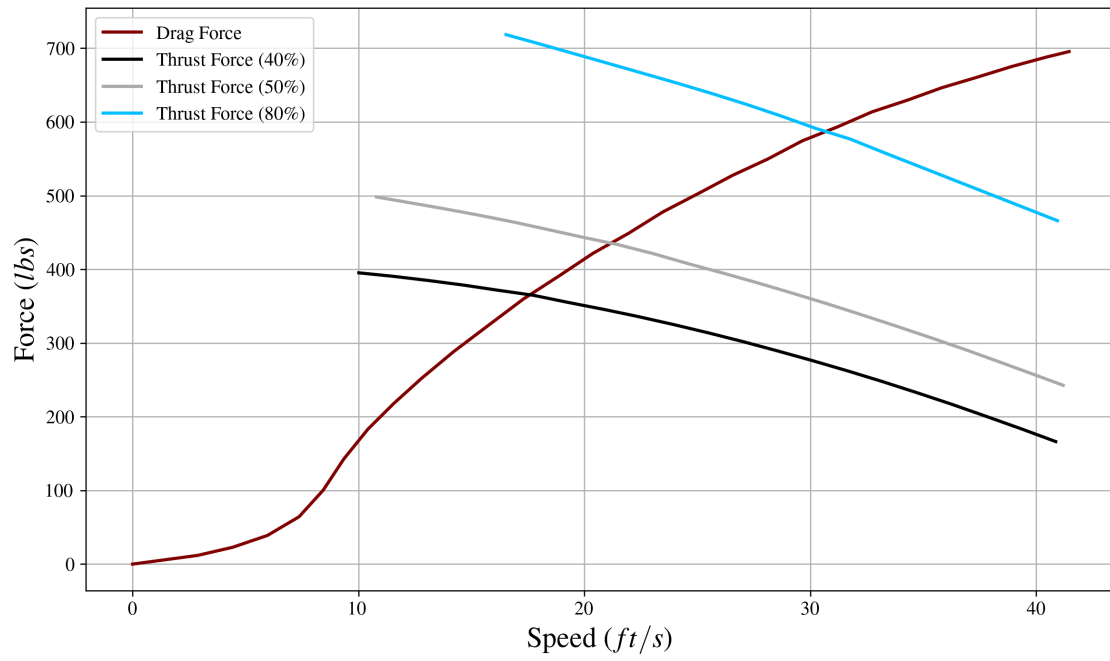
Problem 3

Given
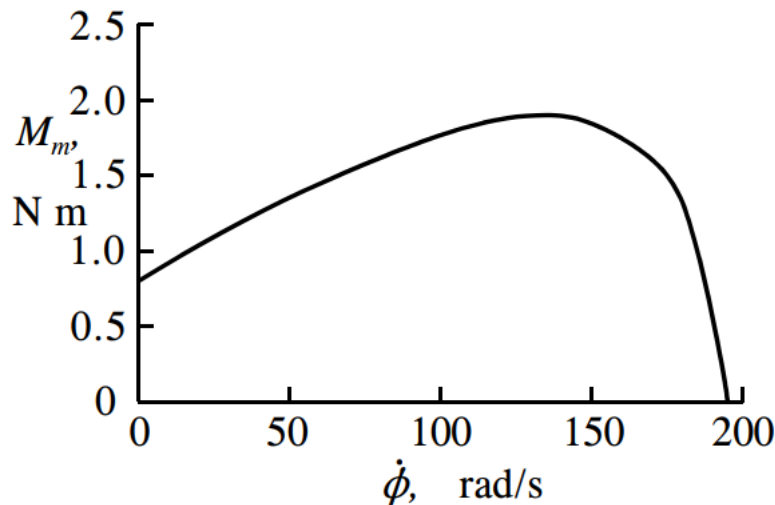
The image above shows the moment curve on a shaft with respect to varying angular velocities.

Find

Estimate the maximum power P_{max} the induction motor can deliver, and the associated torque M and angular velocity $\dot{\theta}$. Also, find the ratio of this power to the power P_{maxM} (power at maximum torque) delivered when the torque is maximized.

Solution

We first need to convert the torque curve into a dataset.

```
[18]: motor_data = pd.read_csv('motor_data.csv')

      max_M = np.max(motor_data['M'])   # N*m
      max_M_theta = np.array(motor_data['theta_dot'])[motor_data['M'] == max_M][0]

      fig, ax = plt.subplots()
      ax.plot(motor_data['theta_dot'], motor_data['M'])
      ax.scatter(max_M_theta, max_M, color='black', label='Max Torque', zorder=3)
      ax.set_xlabel(r'$\dot{\theta}$ ($rad/s$)')
      ax.set_ylabel(r'Torque ($N\cdot m$)')
      ax.legend()
      plt.show()
```
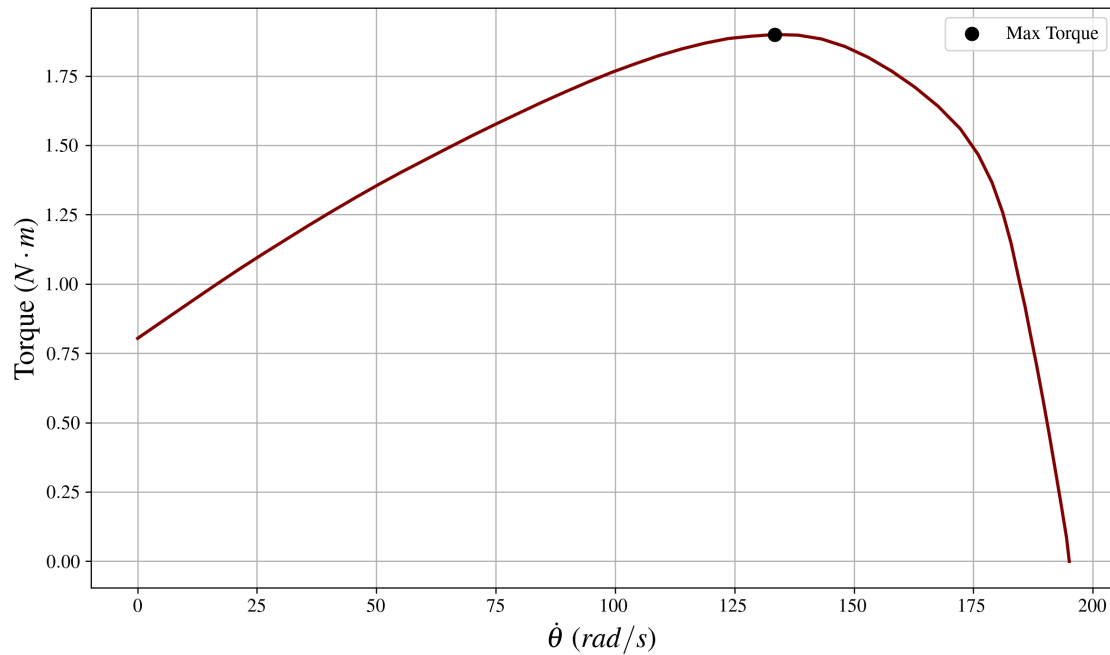
For each point in the dataset, the power is

$$P = M \cdot \dot{\theta}$$

```
[19]: # Getting power
      power = np.array(motor_data['M']*motor_data['theta_dot'])
      P_max = np.max(power)
      max_P_theta = np.array(motor_data['theta_dot'])[power == P_max][0]
      P_max   # W
```

```
[19]: 279.09391404004356
```

```
[20]: # Getting power at maximum torque
      P_maxM = max_M*max_M_theta
      P_maxM   # W
```

```
[20]: 253.51556550997947
```

```
[21]: # Getting the ratio of the two
      P_max/P_maxM
```

```
[21]: 1.1008945879855934
```

Verification

You can see the results are correct on the graph below.

```
[22]: fig, ax = plt.subplots()
      ax.plot(motor_data['theta_dot'], power)
      ax.scatter(max_P_theta, P_max, color='black', label='Max Power', zorder=3)
      ax.scatter(max_M_theta, P_maxM, color='darkgrey', label='Power at Max Torque',␣
       ↪zorder=3)
      ax.set_xlabel(r'$\dot{\theta}$ ($rad/s$)')
      ax.set_ylabel('Power ($W$)')
      ax.legend()
      plt.show()
```