# Case Study # 5: Two-Species Diffusion-Diurnal Kinetics

#### John Karasinski

Graduate Student Researcher
Center for Human/Robotics/Vehicle Integration and Performance
Department of Mechanical and Aerospace Engineering
University of California
Davis, California 95616
Email: karasinski@ucdavis.edu

# 1 Problem Description

Chang et al. [1,2] have proposed approximate models to describe the chemical kinetics and transport phenomena associated with the dissociation of oxygen (O<sub>2</sub>) into ozone (O<sub>3</sub>) and monatomic oxygen (O) in the upper atmosphere. A one-dimensional version of such a model is considered here. The ambient oxygen concentration,  $c_3$ , is constant, while the concentrations of the two minor species, O and O<sub>3</sub>, are  $c_1(z,t)$  and  $c_2(z,t)$ , where z is the elevation above the earth's surface in km (here  $30 \le z \le 50$ ) and t is time in seconds. Their transport is modeled using a reaction-diffusion equation,

$$\frac{\partial c_i}{\partial t} = \frac{\partial}{\partial z} \left[ K(z) \frac{\partial c_i}{\partial z} \right] + R_i(\vec{c}, t) \qquad i = 1, 2, 3.$$
 (1)

The diffusive term is meant to represent the turbulent vertical transport with

$$K(z) = 10^{-8} \cdot exp(z/5)$$
 [km/s], (2)

and the chemistry is described using the Chapman mechanism [2]. The reaction rates,  $R_i(c,t)$ , are given by

$$R_1(c_1, c_2, t) = -k_1c_1c_3 - k_2c_1c_2 + 2k_3(t)c_3 + k_4(t)c_2$$

$$R_2(c_1, c_2, t) = k_1c_1c_3 - k_2c_1c_2 - k_4(t)c_2$$
(3)

with,

$$k_1 = 1.63x10^{16}$$
  
 $k_2 = 4.66x10^{16}$   
 $k_l = \exp[a_l/\sin \omega t]$  if  $\sin \omega t > 0$ , else  $0$   $(l = 3,4)$ 

and with  $a_3 = 22.62$ ,  $a_4 = 7.601$ , and  $\omega = \pi/43200$ . This system is subject to the initial conditions,

$$c_1(z,0) = 10^6 \cdot \gamma(z)$$

$$c_2(z,0) = 10^{12} \cdot \gamma(z),$$
(4)

where

$$\gamma(z) = 1 - \left(\frac{z - 40}{10}\right)^2 + \frac{1}{2} \left(\frac{z - 40}{10}\right)^4,\tag{5}$$

and a boundary condition of no flux at the top and bottom of the vertical atmospheric layer considered.

### 2 Numerical Solution Approach

To generate a system of ordinary differential equations, all the spatial derivatives in Equation 1 are replaced with centered finite differences. For the base case considered, the domain is discretized into M = 50 partitions,  $\Delta z = 20/M$ , and  $z_j = 30 + j(\Delta z)$  for  $0 \le j \le M$ .

The function  $c^{i}(z_{i},t)$  can then be approximated as

$$\dot{c}_{j}^{i} = (\Delta z)^{-2} [K_{j+1/2} c_{j+1}^{i} - (K_{j+1/2} + K_{j-1/2}) c_{j}^{i} + K_{j-1/2} c_{j-1}^{i}] + R^{i}(\boldsymbol{c}, t),$$
(6)

where  $K_{j\pm 1/2} = K(30 + [j \pm 1/2]\Delta z)$ . A system of 2M ODEs is then specified by setting  $\mathbf{y}(t) = [c_1^1(t), c_1^2(t), c_2^1(t), c_2^2(t), \dots, c_M^1(t), c_M^2(t)]^T$ , with boundary conditions  $c_0^i = c_2^i$  and  $c_{M-1}^i = c_{M+1}^i$ . The two parabolic PDEs are then reduced to a system of 2M ODEs of the form  $\dot{\mathbf{y}} = \mathbf{f}(t, \mathbf{y})$ .

Two solvers are called from scipy version 0.11.0 to solve this system of ODEs. A stiff solver, "vode", is an implicit method based on the backward differentiation formulas, and a non-stiff solver, "dopri5", is an explicit Runge-Kutta method of order (4,5) are used.

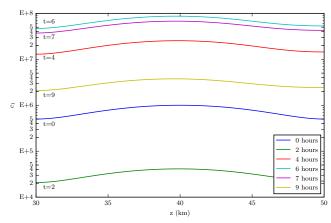


Fig. 1:  $c_1$  vs. z at t = 0, 2, 4, 6, 7, and 9 hours

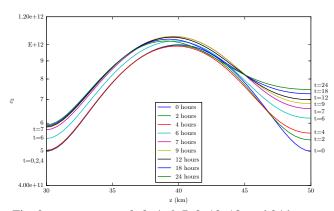


Fig. 2:  $c_2$  vs. z at t = 0, 2, 4, 6, 7, 9, 12, 18, and 24 hours

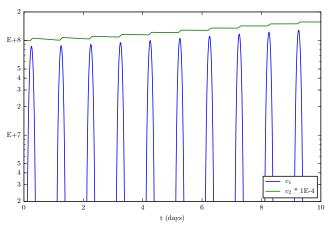


Fig. 3:  $c_1$  and  $c_2$  vs. time (from 0 to 10 days) at z = 40 km,  $c_2$  is scaled by 1E-4

## 3 Results Discussion

#### 3.1 Comparison to Published Results

Both methods required an absolute tolerance of 1E-1 and a relative tolerance 1E-3 for convergence. The results found for both the bdf and dopri5 solvers are effectively the save when plotted on a logarithmic scale. The results from

Solver	24 hours	10 days
dopri5	1025	10069
bdf	1318	13237

Table 1: Wall clock time, in seconds, for each solver to solve to t = 24 hours and t = 10 days

the dopri5 solver can be seen in Figures 1, 2, and 3, and compare well with published results [1, 2].

In particular the ordering of the  $c_1$  concentrations are the same from t=0 to t=9 hours. From highest to lowest concentrations, the ordering is t=6,7,4,9,0, and 2 hours. The ordering of the  $c_2$  concentrations also agree over the time range of t=0 to t=24 hours. From highest to lowest concentrations at the upper boundary of 50 km, the ordering is t=24,18,12,9,7,6,4,2, and 0 hours. Additionally, the concentrations of both species were investigated at a height of 40 km as a function of time. A peak is seen in the concentration of  $c_1$  during each day. This peak grows slightly as time elapses. The concentration of  $c_2$  acts as a step function, stepping up each day at approximately the same time as the  $c_1$  concentration peaks.

The results for concentrations of  $c_1$  and  $c_2$  as a function of altitude, and the results for the concentrations of  $c_1$  and  $c_2$  at 40 km as a function of time agree with the results in both reference papers.

### 3.2 Difference in convergence time

For stiff problems such as this, stiff solvers should take longer to convergence than non-stiff solvers. Table 1 shows the wall clock time, in seconds, to converge for the 24 hour and 10 day cases. The bdf solver takes about 31% longer to converge than the dopri5 solver, suggesting that this problem is indeed stiff.

## 3.3 Sensitivity to Mesh Density

The effect of varying the mesh size was also investigated. The solution was found for the concentrations of both species for both solvers at t = 4 hours using meshes resultant from M = 5, 10, 25, 50, 75, 100, and 200. The solution with the mesh resulting from M = 200 was taken to be effectively equivalent to the analytical solution, and was used as the basis for comparison between the solutions found with the other meshes.

The Root Mean Square error,

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [c_i - c_i^*]^2},$$
 (7)

and the Normalized Root Mean Square error,

$$NRMS = \frac{RMSE}{max(c_i^*) - min(c_i^*)},$$
(8)

M	$c_1$	$c_2$
5	1.628E-2	1.648E-2
10	9.766E-3	9.829E-3
25	4.178E-3	4.110E-3
50	1.879E-3	1.811E-3
75	1.031E-3	9.806E-4
100	6.923E-4	6.098E-4

Table 2: NRMS of results at t = 4 hours compared to results at M = 200 for the dopri5 solver

M	$c_1$	$c_2$
5	1.654E-2	1.648E-2
10	9.796E-3	9.829E-3
25	4.091E-3	4.110E-3
50	1.802E-3	1.811E-3
75	9.436E-4	9.806E-4
100	5.982E-4	6.098E-4

Table 3: NRMS of results at t = 4 hours compared to results at M = 200 for the bdf solver

can be calculated. Here  $c_i$  is the result for the the concentration of each species i at each point on the 1-D domain generated from each value for M,  $c_i^*$  is the solution from the M = 200 simulation, and N is the number of points on the 1-D domain. The *NRMS* for each case is expressed as a percentage, where lower values indicate a result closer to the analytic solution. For the complete NRMS results for each solver and mesh, see Tables 2 and 3.

These results show that the difference between the meshes decreases rapidly for larger M. At M=50, the NRMS is around 1.8E-3 for both concentrations using both solvers. This relatively low value indicates that using a mesh from M=50 leads to relatively good results with the benefit of a reduced solver time. A plot of these results can be seen as Figure 4.

#### 4 Conclusion

A previously developed model to describe the chemical kinetics and transport phenomena associated with the dissociation of oxygen in the upper atmosphere was investigated and the results were compared to previously published results. A numerical solution of the system was discretized using the method of lines and central differencing for the diffusion term on a uniform mesh with M nodes.

A Python script was created and scipy was used to call both a stiff and non-stiff ODE solver to investigate the concentrations of two species of oxygen as a function of altitude

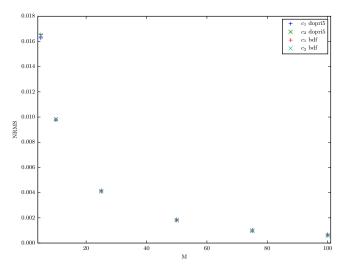


Fig. 4: NRMS for M = 5, 10, 25, 50, 75, and 100 compared against M = 200 for both solvers and concentrations

and time. This script can be seen as Appendix 1. The results of these two solvers both compared well to previously published results, though the stiff solver took approximately 31% longer to converge. A mesh sensitivity study was also performed, and confirmed that the base mesh resulting from M = 50 was adequate for the values investigated here.

#### References

- [1] Chang, J., Hindmarsh, A., and Madsen, N., 1974. "Simulation of chemical kinetics transport in the stratosphere". In *Stiff differential systems*. Springer, pp. 51–65.
- [2] Byrne, G. D., and Hindmarsh, A. C., 1987. "Stiff ode solvers: A review of current and coming attractions". *Journal of Computational Physics*, 70(1), pp. 1–62.

## Appendix A: Python Code

```
import numpy as np
2 from scipy.integrate import ode
 from time import clock
  from PrettyPlots import *
  def K(j):
      return 1E-8 * np.exp((30. + j * dz) / 5.)
11 def gamma(z):
      return 1. - ((z - 40.) / 10.) ** 2 + (1. / 2.) * ((z - 40.) / 10.) ** 4
13
  def R(y_1, y_2, t):
15
      if np.sin(w * t) > 0.:
16
          k_3 = np.exp(-a_3 / np.sin(w * t))
17
18
          k_4 = np.exp(-a_4 / np.sin(w * t))
19
      else:
          k_3 = 0.
20
          k_4 = 0.
23
      R_1 = -k_1 * y_1 * y_3 - k_2 * y_1 * y_2 + 2. * k_3 * y_3 + k_4 * y_2
      R_2 = +k_1 * y_1 * y_3 - k_2 * y_1 * y_2 - k_4 * y_2
      return R_1, R_2
25
27
  def system(t, y):
28
      f = np.zeros(len(y))
29
30
      R1, R2 = R(y[0], y[1], t)
32
      l_p, l_m = 3. / 2., 1. / 2.
      f[0] = (dz ** -2 * (K(1_p) * y[2] - (K(1_p) + K(1_m)) * y[0] + K(1_m) * y[2]) + R1)
34
      f[1] = (dz ** -2 * (K(1_p) * y[3] - (K(1_p) + K(1_m)) * y[1] + K(1_m) * y[3]) + R2)
35
36
      for i in range(1, M):
          R1, R2 = R(y[2 * i], y[2 * i + 1], t)
38
39
          l_p, l_m = i + 3. / 2., i + 1. / 2.
          f[2 * i] =
                         (dz ** -2 * (K(l_p) * y[2 * i + 2] -
41
                           (K(l_p) + K(l_m)) * y[2 * i] + K(l_m) * y[2 * i - 2]) + R1)
40
          f[2 * i + 1] = (dz * * -2 * (K(l_p) * y[2 * i + 3] -
43
                           (K(l_p) + K(l_m)) * y[2 * i + 1] + K(l_m) * y[2 * i - 1]) + R2)
45
      R1, R2 = R(y[2 * M], y[2 * M + 1], t)
46
      l_p, l_m = M + 1. / 2., M - 1. / 2.
47
48
                    = (dz ** -2 * (K(1_p) * y[2 * M - 2] - (K(1_p) + K(1_m)) * y[2 * M] + K(1_m) * y[2 * M - 2]) + R1) 
      f[2 * M]
49
50
      f[2 * M + 1] = (dz ** -2 * (K(1_p) * y[2 * M - 1] -
                       (K(l_p) + K(l_m)) * y[2 * M + 1] + K(l_m) * y[2 * M - 1]) + R2)
52
53
54
      return f
55
  def solve(solver, c, time, integrator):
57
      # Create result arrays
      c1, c2, c1_40km, c2_40km, t = [], [], [], [], []
59
60
      start_time = clock()
61
      for i in range(0, len(time) - 1):
63
         # Initial and final time
          t_0 = time[i]
64
          t_f = time[i + 1]
65
66
          # Solver setup
```

```
sol = []
69
           solver.set_initial_value(c, t_0)
           while solver.successful() and solver.t < t_f:</pre>
               solver.integrate(solver.t + dt)
               sol.append(solver.y)
               # Keep time history for 40km point
74
               one, two = sol[-1][0::2], sol[-1][1::2]
               mid\_one, mid\_two = one[M / 2], two[M / 2]
76
               c1_40km.append(mid_one), c2_40km.append(mid_two)
78
               t.append(solver.t)
79
               print "{0:03.2f}%".format(100. * solver.t / time[-1])
80
81
           # Save c1, c2 solutions
82
           c1.append(one), c2.append(two)
83
           # Update initial conditions for next iteration
8.5
           c = sol[-1]
86
87
88
       elapsed_time = clock() - start_time
       print(elapsed_time, "seconds process time")
89
90
       output = [c1, c2, c1_40km, c2_40km, t]
91
       return output
92
93
94
   def save_variables(name, z, c1, c2, t, c1_40km, c2_40km):
95
96
97
           os.mkdir('data')
98
       except Exception:
99
          pass
100
101
           os.mkdir('data/' + name)
102
       except Exception:
103
          pass
104
105
       np.savetxt('data/' + name + '/z.csv', z)
106
       np.savetxt('data/' + name + '/c1.csv', c1)
107
       np.savetxt('data/' + name + '/c2.csv', c2)
108
       np.savetxt('data/' + name + '/t.csv', t)
109
       np.savetxt('data/' + name + '/c1_40km.csv', c1_40km)
110
       np.savetxt('data/' + name + '/c2_40km.csv', c2_40km)
114
  def load_variables(name):
               = np.loadtxt('data/' + name + '/z.csv')
115
               = np.loadtxt('data/' + name + '/cl.csv')
       c1
      c2
               = np.loadtxt('data/' + name + '/c2.csv')
               = np.loadtxt('data/' + name + '/t.csv')
118
      c1_40km = np.loadtxt('data/' + name + '/c1_40km.csv')
119
      c2_40km = np.loadtxt('data/' + name + '/c2_40km.csv')
120
       return z, c1, c2, t, c1_40km, c2_40km
  def run_trials(z, integrators, times, M):
125
       # Set up ODE solver
126
       for integrator in integrators:
127
128
           if integrator == 'dop853' or integrator == 'dopri5':
               solver = ode(system)
129
               solver.set_integrator(integrator, atol=1E-1, rtol=1E-3)
130
           elif integrator == 'bdf':
131
               solver = ode(system)
               \verb|solver.set_integrator| (\verb|vode||, method=integrator|, atol=1E-1|, rtol=1E-3|, nsteps=2000|) \\
133
134
           name = integrator + ' ' + str(times[-1]) + ' ' + str(M)
           try:
```

```
z, c1, c2, t, c1_40km, c2_40km = load_variables(name)
138
               print "Loaded data for: " + name
139
           except:
               print "Starting solver: ", integrator, "with times", times
140
               c1, c2, c1_40km, c2_40km, t = solve(solver, c, times, integrator)
141
               save_variables(name, z, c1, c2, t, c1_40km, c2_40km)
142
143
           # And plot some things
144
           if times[-1] == 86400.0:
144
               labels = [str(int(time / 3600.)) + " hours" for time in times[1:]]
146
147
               plot_c1(z, c, c1, labels, name)
               plot_c2(z, c, c2, labels, name)
149
           elif times[-1] == 864000.0:
               plot_40km(t, c1_40km, c2_40km, name)
150
153
   def sensitivity_analysis(integrators, times, meshes):
       plt.figure()
154
       for integrator in integrators:
156
           z_M, c1_M, c2_M = [], []
157
           for M in meshes:
158
               name = integrator + ' ' + str(times[-1]) + ' ' + str(M)
160
                   z, c1, c2, _, _, = load_variables(name)
161
162
               except Exception:
                   print Exception
163
               z_M.append(list(z))
164
165
               c1_M.append(list(c1[-1]))
               c2_M.append(list(c2[-1]))
166
167
168
           best_z = z_M[-1]
           best_c1, best_c2 = c1_M[-1], c2_M[-1]
169
           NRMS1, NRMS2 = [], []
170
171
           for j, mesh in enumerate(z_M):
               if j + 1 == len(z_M): break # RMS with yourself is silly
               best1, best2, curr1, curr2 = [], [], [], []
               for i, element in enumerate(best_z):
                   if element in mesh:
                       best1.append(best_c1[i])
176
                       best2.append(best_c2[i])
178
                        curr1.append(c1_M[j][mesh.index(element)])
                        curr2.append(c2_M[j][mesh.index(element)])
179
180
               best1, best2 = np.array(best1), np.array(best2)
181
182
               curr1, curr2 = np.array(curr1), np.array(curr2)
183
184
               err1, err2 = curr1 - best1, curr2 - best2
               NRMS1.append(np.sqrt(np.mean(np.square(errl)))/(max(best1) - min(best1)))
184
               NRMS2.append(np.sqrt(np.mean(np.square(err2)))/(max(best2) - min(best2)))
186
187
188
           x = [mesh for mesh in meshes][0:-1]
           plt.plot(x, NRMS1, '+', label='$c_1$' + integrator)
189
           plt.plot(x, NRMS2, 'x', label='$c_2$' + integrator)
190
191
      plt.ylabel('NRMS')
192
       plt.xlabel('M')
193
194
       plt.xlim([meshes[0] - 1, meshes[-2] + 1])
       plt.legend()
195
       save_name = str(meshes) + '.pdf'
196
197
       save_plot(save_name)
198
199
200 # Basic problem parameters
y_3 = 3.7E16
                        # Concentration of O_2 (constant)
                        # Reaction rate [0 + 0_2 -> 0_3]
202 k_1 = 1.63E-16
203 | k_2 = 4.66E-16
                        # Reaction rate [0 + 0_3 -> 2 * 0_2]
a_{204} = 22.62
                        # Constant used in calculation of k_3
a_4 = 7.601
                        # Constant used in calculation of k_4
```

```
w = \text{np.pi} / 43200. # Cycle (half a day) [1/sec]
207 dt = 60.
                         # seconds
208
209 # Base Case
_{210} M = 50
                        # Number of sections
211 dz = 20. / M
                        # 20km divided by M subsections
212
213 # This generates the initial conditions
c = \text{np.zeros}(2 * (M + 1))
z = np.zeros(M + 1)
216 for i in range(0, M + 1):
     z[i] = 30. + i * dz
218
      c[2 * i] = 1E6 * gamma(z[i])
      c[2 * i + 1] = 1E12 * gamma(z[i])
219
220
221 # Run the trials
222 integrators = ['dopri5', 'bdf']
223 times = 3600. * np.array([0., 2., 4., 6., 7., 9., 12., 18., 24.])
224 run_trials(z, integrators, times, M)
225
integrators = ['dopri5', 'bdf']
227 times = 3600. * np.array([0., 2., 4., 6., 7., 9., 12., 18., 240.])
228 run_trials(z, integrators, times, M)
229
230 # Mesh Analysis
meshes = [5, 10, 25, 50, 75, 100, 200]
232 for M in meshes:
      dz = 20. / M
                            # 20km divided by M subsections
234
235
      # This generates the initial conditions
      c = np.zeros(2 * (M + 1))
236
      z = np.zeros(M + 1)
       for i in range (0, M + 1):
238
           z[i] = 30. + i * dz
239
           c[2 * i] = 1E6 * gamma(z[i])
240
          c[2 * i + 1] = 1E12 * gamma(z[i])
241
242
       # Time array
243
244
      dt = 60.
245
       integrators = ['dopri5', 'bdf']
246
       times = 3600. * np.array([0., 2., 4.])
247
       run_trials(z, integrators, times, M)
249
  sensitivity_analysis(integrators, times, meshes)
```

Listing 1: Code to create solutions

```
import numpy as np
  import matplotlib
  matplotlib.use('TkAgg')
  import matplotlib.pyplot as plt
 import os
 # Configure figures for production
  WIDTH = 495.0  # the number latex spits out
  FACTOR = 1.0  # the fraction of the width the figure should occupy
 fig_width_pt = WIDTH * FACTOR
10
inches_per_pt = 1.0 / 72.27
 golden_ratio = (np.sqrt(5) - 1.0) / 2.0
                                             # because it looks good
14 fig_width_in = fig_width_pt * inches_per_pt # figure width in inches
IS fig_height_in = fig_width_in * golden_ratio # figure height in inches
16 fig_dims = [fig_width_in, fig_height_in] # fig dims as a list
18
def save_plot(save_name):
     # Save plots
20
      try:
```

```
os.mkdir('figures')
       except Exception:
24
          pass
25
       plt.savefig('figures/' + save_name, bbox_inches='tight')
26
       plt.close()
27
28
29
  def plot_c1(z, initial, c1, labels, integrator):
30
      plt.figure(figsize=fig_dims)
31
32
       plt.plot(z, initial[0::2], label='0 hours')
       for solution, label in zip(c1, labels):
           if "12" in label:
34
                break
35
           plt.plot(z, solution, label=label)
36
      plt.ylabel('$c_1$')
       plt.xlabel('z (km)')
38
       plt.yscale('log')
39
      plt.ylim([1E4, 1E8])
40
41
       plt.yticks([1E4, 2E4, 3E4, 4E4, 5E4,
42
                     1E5, 2E5, 3E5, 4E5, 5E5,
                     1E6, 2E6, 3E6, 4E6, 5E6,
43
                     1E7, 2E7, 3E7, 4E7, 5E7, 1E8],
44
                    ['E+4', '2', '3', '4', '5',
45
                     'E+5', '2', '3', '4', '5',
                     'E+6', '2', '3', '4', '5',
47
                     'E+7', '2', '3', '4', '5', 'E+8'])
48
       plt.legend(loc='lower right')
49
50
       plt.text(30.5, 1.5e+4, 't=2', fontsize=9, family='serif')
51
       plt.text(30.5, 3.5e+5, 't=0', fontsize=9, family='serif')
52
       plt.text(30.5, 1.5e+6, 't=9', fontsize=9, family='serif')
       plt.text(30.5, 1.e+7, 't=4', fontsize=9, family='serif')
plt.text(30.5, 2.8e+7, 't=7', fontsize=9, family='serif')
54
55
       plt.text(30.5, 6.e+7, 't=6', fontsize=9, family='serif')
56
57
      save_name = integrator + ' c1.pdf'
58
59
       save_plot(save_name)
60
61
  def plot_c2(z, initial, c2, labels, integrator):
62
       plt.figure(figsize=fig_dims)
63
       plt.plot(z, initial[1::2], label='0 hours')
64
       for solution, label in zip(c2, labels):
65
           if "240" in label:
66
67
                break
68
           plt.plot(z, solution, label=label)
69
       plt.ylabel('$c_2$')
       plt.xlabel('z (km)')
70
       plt.yscale('log')
       plt.ylim([4.E11, 1.2E12])
72
       plt.yticks([4E11, 5E11, 6E11, 7E11, 8E11, 9E11, 1E12, 1.2E12],
                   ['4.00e+11', '5', '6', '7', '8', '9', 'E+12', '1.20e+12'])
      plt.legend(loc='best')
       # Left side text
77
       plt.text(28.25, 4.65e+11, 't=0,2,4', fontsize=9, family='serif')
78
       plt.text(29, 5.4e+11, ^{\prime}t=6^{\prime}, fontsize=9, family=^{\prime}serif^{\prime})
79
       plt.text(29, 5.7e+11,
                                     't=7',
                                                fontsize=9, family='serif')
80
81
82
       # Right side text
       plt.text(50.25, 4.95e+11, 't=0', fontsize=9, family='serif')
83
       plt.text(50.25, 5.35e+11, 't=2', fontsize=9, family='serif')
84
       plt.text(50.25, 5.6e+11, 't=4', fontsize=9, family='serif')
85
      plt.text(50.25, 6.1e+11, 't=6', fontsize=9, family='serif')
      plt.text(50.25, 6.4e+11, 't=7', fontsize=9, family='serif')
plt.text(50.25, 6.7e+11, 't=9', fontsize=9, family='serif')
plt.text(50.25, 7.0e+11, 't=12', fontsize=9, family='serif')
plt.text(50.25, 7.3e+11, 't=18', fontsize=9, family='serif')
87
88
89
```

```
91
      plt.text(50.25, 7.6e+11, 't=24', fontsize=9, family='serif')
92
      save_name = integrator + ' c2.pdf'
93
      save_plot(save_name)
94
95
96
97
  def plot_40km(t, c1_40km, c2_40km, integrator):
      c2_{40km\_scaled} = [1E-4 * val for val in c2_{40km}]
      days = [val / 86400. for val in t]
99
100
101
      plt.figure(figsize=fig_dims)
      plt.plot(days, c1_40km, label='$c_1$')
102
      plt.plot(days, c2_40km_scaled, label='c_2 * 1E-4')
103
      plt.xlabel('t (days)')
104
      plt.yscale('log')
105
106
      plt.ylim([2.E6, 2E8])
107
      plt.yticks([2E6, 3E6, 4E6, 5E6, 1E7, 2E7, 3E7, 4E7, 5E7, 1E8, 2E8],
                  ['2', '3', '4', '5', 'E+7', '2', '3', '4', '5', 'E+8', '2'])
108
      plt.xlim([0, days[-1]])
109
      plt.legend(loc='lower right')
110
      save_name = integrator + ' time.pdf'
      save_plot(save_name)
```

Listing 2: Code to generate pretty plots