	<pre># Solve tau dx/dt = -x import numpy as np from numpy.linalg import inv  ## problem statement x0 = 3.0 # initial condition tf = 10.0 # final time tau = 5.0 # model parameter (time constant)  ## analytic solution time = np.linspace(0,tf,100)</pre>
	<pre>time = np.linspace(0,tf,100) x = x0*np.exp(-time/tau)  ## numeric solutions # 2nd order polynomial (3 points) t2 = tf * np.array([0.0,0.5,1.0]) N2 = np.array([[0.75,-0.25], \</pre>
	<pre>v2 = np.dot(Q2, np.ones(2)*x0) x2 = np.insert(v2,0,x0)  # 3rd order polynomial (4 points) t3 = tf * np.array([0.0, \</pre>
	<pre>[0.603, 0.230, 0.167]]) M3 = inv(tf * N3) # Solve linear system of equations by matrix manipulation P3 = tau * M3 + np.eye(3) Q3 = np.dot(inv(P3), (tau*M3)) v3 = np.dot(Q3, np.ones(3)*x0) x3 = np.insert(v3,0,x0)  # 4th order polynomial (5 points) t4 = tf * np.array([0.0, \</pre>
	1.0/2.0, \ 1.0/2.0+np.sqrt(21.0)/14.0, \ 1.0])  N4 = np.array([[0.278, -0.202, 0.169, -0.071], \ [0.398, 0.069, 0.064, -0.031], \ [0.387, 0.234, 0.278, -0.071], \ [0.389, 0.222, 0.389, 0.000]])  M4 = inv(tf * N4)  # Solve linear system of equations by matrix manipulation P4 = tau * M4 + np.eye(4) Q4 = np.dot(inv(P4),(tau*M4))
	<pre>v4 = np.dot(Q4, np.ones(4)*x0) x4 = np.insert(v4,0,x0)  # compare results import matplotlib.pyplot as plt plt.figure(1) plt.subplot(2,1,1) plt.plot(time,x,'r-',linewidth=3) plt.plot(t2,x2,'b',linewidth=2,markersize=20) plt.plot(t3,x3,'k:.',linewidth=2,markersize=20) plt.plot(t4,x4,'g',linewidth=2,markersize=20)</pre>
	<pre>plt.xlabel('Time') plt.ylabel('Value') plt.legend(['Exact','3 Points','4 Points','5 Points']) plt.text(2,0.5,'tau dx/dt = -x')  plt.subplot(2,1,2) # exact solutions at collocation points y2 = x0*np.exp(-t2/tau) y3 = x0*np.exp(-t3/tau) y4 = x0*np.exp(-t4/tau) plt.plot(t2,x2-y2,'b',linewidth=2,markersize=20) plt.plot(t3,x3-y3,'k:.',linewidth=2,markersize=20)</pre>
	<pre>plt.plot(t4,x4-y4,'g',linewidth=2,markersize=20) plt.xlabel('Time') plt.ylabel('Error') plt.legend(['3 Points','4 Points','5 Points']) plt.show()</pre> Exact
	1 tau dx/dt = -x 0 2 4 6 8 10  3 Points 4 Points 5 Points  1 Time
In [3]:	#@markdown ###Orthogonal Collocation 2  # Solve tau dx/dt = -x + k u import numpy as np from numpy.linalg import inv  ## problem statement x0 = 0.0 # initial condition tf = 10.0 # final time
	<pre>tau = 5.0 # model parameter (time constant) k = 2.0 # gain  ## analytic solution time = np.linspace(0,tf) x = k*(1.0-np.exp(-time/tau))  ## numeric solutions # 2nd order polynomial (3 points) t2 = tf * np.array([0.0,0.5,1.0]) N2 = np.array([[0.75,-0.25], \)</pre>
	<pre>[1.00, 0.00]]) M2 = inv(tf * N2) # Solve linear system of equations by matrix manipulation P2 = inv(tau*M2 + np.eye(2)) Q2 = np.dot(tau*M2,np.ones(2)*x0) + k*np.ones(2) v2 = np.dot(P2, Q2) x2 = np.insert(v2,0,x0) # 3rd order polynomial (4 points) t3 = tf * np.array([0.0, \</pre>
	<pre>1.0/2.0+np.sqrt(5.0)/10.0, \</pre>
	<pre># 4th order polynomial (5 points) t4 = tf * np.array([0.0, \</pre>
	<pre>M4 = inv(tf * N4) # Solve linear system of equations by matrix manipulation P4 = inv(tau*M4 + np.eye(4)) Q4 = np.dot(tau*M4,np.ones(4)*x0) + k*np.ones(4) v4 = np.dot(P4, Q4) x4 = np.insert(v4,0,x0) # compare results import matplotlib.pyplot as plt plt.figure(1) plt.subplot(2,1,1)</pre>
	<pre>plt.plot(time,x,'r-',linewidth=3) plt.plot(t2,x2,'b',linewidth=2,markersize=20) plt.plot(t3,x3,'k:.',linewidth=2,markersize=20) plt.plot(t4,x4,'g',linewidth=2,markersize=20) plt.xlabel('Time') plt.ylabel('Value') plt.legend(['Exact','3 Points','4 Points','5 Points']) plt.text(4,0.5,'tau dx/dt = -x + k u')  plt.subplot(2,1,2) # exact solutions at collocation points</pre>
	<pre>y2 = k*(1-np.exp(-t2/tau)) y3 = k*(1-np.exp(-t3/tau)) y4 = k*(1-np.exp(-t4/tau)) plt.plot(t2,x2-y2,'b',linewidth=2,markersize=20) plt.plot(t3,x3-y3,'k:.',linewidth=2,markersize=20) plt.plot(t4,x4-y4,'g',linewidth=2,markersize=20) plt.xlabel('Time') plt.ylabel('Error') plt.legend(['3 Points','4 Points','5 Points']) plt.show()</pre>
	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
(	Exercise 1  Objective: Solve a differential equation with orthogonal collocation on finite elements. Create a MATLAB or Python script to simulate and
; 1 ;	display the results. Estimated Time: 2-3 hours Solve the following differential equation from time 0 to 1 with orthogonal collocation on finite elements with 4 nodes for discretization in time.
In [31]:	<pre>import numpy as np from scipy.optimize import fsolve from scipy.integrate import odeint import matplotlib.pyplot as plt  # final time tf = 5.0  # solve with ODEINT (for comparison) def model(x,t):</pre>
	<pre>der model(x,t):     u = 4.0     return (-x**2 + u)/5.0  t = np.linspace(0,tf,20) y0 = 0 y = odeint(model,y0,t) plt.figure(1) plt.plot(t,y,'r-',label='ODEINT')  #</pre>
	<pre># define collocation matrices  def colloc(n):     if (n==2):         NC = np.array([[1.0]])     if (n==3):         NC = np.array([[0.75,-0.25], \</pre>
	<pre>[0.603, 0.230, 0.167]])  if (n==5):     NC = np.array([[0.278, -0.202, 0.169, -0.071], \</pre>
	<pre>[0.269, 0.181, 0.374, 0.110, 0.067]]) return NC  # define collocation points from Lobatto quadrature def tc(n):     if (n==2):         time = np.array([0.0,1.0])     if (n==3):         time = np.array([0.0,0.5,1.0])     if (n==4):         time = np.array([0.0, \</pre>
	<pre>0.5-np.sqrt(5)/10.0, \ 0.5+np.sqrt(5)/10.0, \ 1.0])  if (n==5):     time = np.array([0.0,0.5-np.sqrt(21)/14.0, \ 0.5,0.5+np.sqrt(21)/14.0, 1])  if (n==6):     time = np.array([0.0, \ 0.5-np.sqrt((7.0+2.0*np.sqrt(7.0))/21.0)/2.0, \ 0.5-np.sqrt((7.0-2.0*np.sqrt(7.0))/21.0)/2.0, \ 0.5+np.sqrt((7.0-2.0*np.sqrt(7.0))/21.0)/2.0, \ 0.5+np.sqrt((7.0-2.0*np.sqrt(7.0))/21.0)/2.0, \</pre>
	<pre>0.5+np.sqrt((7.0-2.0*np.sqrt(7.0))/21.0)/2.0, \</pre>
	<pre>xdot[0:n-1] = z[n-1:m]  # initial condition (x0) x0 = 0.0 # input parameter (u) u = 4.0 # final time tn = tf  # function evaluation residuals</pre>
	<pre>F = np.empty(m) # nonlinear differential equations at each node # 5 dx/dt = -x^2 + u F[0:n-1] = 5.0 * xdot[0:n-1] + x[0:n-1]**2 - u # collocation equations # tn * NC * xdot = x - x0 NC = colloc(n) F[n-1:m] = tn * np.dot(NC, xdot) - x + x0 * np.ones(n-1) return F</pre> sol_py = np.empty(5) # store 5 results
	<pre>for i in range(2,7):     n = i     m = (i-1)*2     zGuess = np.ones(m)     z = fsolve(myFunction, zGuess, args=(n,m))     # add to plot     yc = np.insert(z[0:n-1],0,0)     plt.plot(tc(n),yc,'o',markersize=10,label='Nodes = '+str(i))     # store just the last x[n] value     sol_py[i-2] = z[n-2] plt.legend(loc='best')</pre>
	<pre>#</pre>
	<pre>m = GEKKO()  u = m.Param(value=4) x = m.Var(value=0) m.Equation(5*x.dt() == -x**2 + u)  m.time = [0,tf]  m.options.imode = 4 m.options.time_shift = 0 m.options.nodes = nodes</pre>
	<pre>m.solve() # solve problem     sol_apm[i] = x.value[-1] # store solution (last point)     i += 1  # print the solutions print(sol_py) print(sol_apm)  # show plot plt.ylabel('x(t)')</pre>
	plt.xlabel('time') plt.show()  apm 10.32.114.116_gk_model20 APMonitor, Version 1.0.1 APMonitor Optimization Suite
	Objects : 0 Constants : 0 Variables : 2 Intermediates: 0 Connections : 0 Equations : 1 Residuals : 1  Variable time shift OFF Number of state variables: 2 Number of total equations: - 2
	Number of slack variables: - 0  Degrees of freedom : 0  **********************************
	**************************************
	Total number of variables
	<pre>iter</pre>
	Objective       0.00000000000000000000000000000000000
	Number of equality constraint Jacobian evaluations = 5  Number of inequality constraint Jacobian evaluations = 0  Number of Lagrangian Hessian evaluations = 4  Total CPU secs in IPOPT (w/o function evaluations) = 0.003  Total CPU secs in NLP function evaluations = 0.000  EXIT: Optimal Solution Found.  The solution was found.  The final value of the objective function is 0.0000000000000000000000000000000000
	The Thial value of the Objective Tunction is 0.0000000000000000000000000000000000
	Equations: 1 Residuals: 1  Variable time shift OFF  Number of state variables: 4  Number of total equations: - 4  Number of slack variables: - 0  Degrees of freedom: 0
	Dynamic Simulation with Interior Point Solver  ***********************************
	This is Ipopt version 3.12.10, running with linear solver ma57.  Number of nonzeros in equality constraint Jacobian: 9  Number of nonzeros in inequality constraint Jacobian.: 0  Number of nonzeros in Lagrangian Hessian
	Total number of inequality constraints
	5 0.0000000e+00 2.44e-13 0.00e+00 -11.0 4.93e-07 - 1.00e+00 1.00e+00h 1  Number of Iterations: 5  (scaled) (unscaled)  Objective: 0.000000000000000e+00 0.0000000000000e+00  Dual infeasibility: 0.000000000000000e+00 0.000000000000000
	Number of objective function evaluations = 8 Number of objective gradient evaluations = 6 Number of equality constraint evaluations = 8 Number of inequality constraint evaluations = 0 Number of equality constraint Jacobian evaluations = 6 Number of inequality constraint Jacobian evaluations = 0 Number of Lagrangian Hessian evaluations = 5 Total CPU secs in IPOPT (w/o function evaluations) = 0.0002 Total CPU secs in NLP function evaluations = 0.0000
	EXIT: Optimal Solution Found.  The solution was found.  The final value of the objective function is 0.0000000000000000000000000000000000
	Successful solution
	Objects : 0 Constants : 0 Variables : 2 Intermediates: 0 Connections : 0 Equations : 1 Residuals : 1  Variable time shift OFF Number of state variables: 6 Number of total equations: - 6
	Number of slack variables: - 0  Degrees of freedom : 0  **********************************
	**************************************
	Number of nonzeros in Lagrangian Hessian: 3  Total number of variables
	<pre>iter objective inf_pr inf_du lg(mu)   d   lg(rg) alpha_du alpha_pr ls     0 0.0000000e+00 4.00e+00 0.00e+00 0.0 0.00e+00 - 0.00e+00 0.00e+00 0  Reallocating memory for MA57: lfact (277)     1 0.0000000e+00 6.83e+00 0.00e+00 -11.0 4.00e+00 - 1.00e+00 1.00e+00H 1     2 0.0000000e+00 8.32e-01 0.00e+00 -11.0 9.12e-01 - 1.00e+00 1.00e+00H 1     3 0.0000000e+00 7.77e-03 0.00e+00 -11.0 9.52e-02 - 1.00e+00 1.00e+00h 1     4 0.0000000e+00 5.79e-06 0.00e+00 -11.0 2.41e-03 - 1.00e+00 1.00e+00h 1     5 0.0000000e+00 2.56e-12 0.00e+00 -11.0 1.60e-06 - 1.00e+00 1.00e+00h 1</pre>
	(scaled) (unscaled)  Objective
	Number of equality constraint evaluations = 8  Number of inequality constraint evaluations = 0  Number of equality constraint Jacobian evaluations = 6  Number of inequality constraint Jacobian evaluations = 0  Number of Lagrangian Hessian evaluations = 5  Total CPU secs in IPOPT (w/o function evaluations) = 0.003  Total CPU secs in NLP function evaluations = 0.000  EXIT: Optimal Solution Found.
	The final value of the objective function is 0.0000000000000000000000000000000000
	APMonitor, Version 1.0.1  APMonitor Optimization Suite
	Connections: 0 Equations: 1 Residuals: 1  Variable time shift OFF Number of state variables: 8 Number of total equations: - 8 Number of slack variables: - 0 Degrees of freedom: 0
	**************************************
	For more information visit http://projects.coin-or.org/Ipopt ***********************************
	variables with only upper bounds: 0  Total number of equality constraints
	1
	Overall NLP error: 7.6675927906943997e-07 7.6675927906943997e-07  Number of objective function evaluations = 9 Number of objective gradient evaluations = 5 Number of equality constraint evaluations = 9 Number of inequality constraint evaluations = 0 Number of equality constraint Jacobian evaluations = 5 Number of inequality constraint Jacobian evaluations = 5 Number of inequality constraint Jacobian evaluations = 0 Number of Lagrangian Hessian evaluations = 4
	Number of Lagrangian Hessian evaluations = 4  Total CPU secs in IPOPT (w/o function evaluations) = 0.003  Total CPU secs in NLP function evaluations = 0.001  EXIT: Optimal Solution Found.  The solution was found.  The final value of the objective function is 0.0000000000000000000000000000000000
	Solution time : 6.799999999202555E-003 sec Objective : 0.00000000000000E+000 Successful solution
	Each time step contains  Objects : 0  Constants : 0  Variables : 2  Intermediates: 0  Connections : 0  Equations : 1  Residuals : 1  Variable time shift OFF  Number of state variables: 10
	**************************************
	Number of nonzeros in inequality constraint Jacobian:: 0 Number of nonzeros in Lagrangian Hessian: 5  Total number of variables
	(scaled) (unscaled)  Objective: 0.000000000000000000000000000000
	Number of objective gradient evaluations = 5 Number of equality constraint evaluations = 7 Number of inequality constraint evaluations = 0 Number of equality constraint Jacobian evaluations = 5 Number of inequality constraint Jacobian evaluations = 0 Number of Lagrangian Hessian evaluations = 4 Total CPU secs in IPOPT (w/o function evaluations) = 0.003 Total CPU secs in NLP function evaluations = 0.001  EXIT: Optimal Solution Found.
	The final value of the objective function is 0.0000000000000000000000000000000000
	[1.56155281 1.95898339 1.93126998 1.9301535 1.92970515] [1.56155284 1.95898339 1.93159986 1.93034749 1.9282544 ]  2.00 1.75 Nodes = 2 Nodes = 3 Nodes = 4 Nodes = 5 Nodes = 6
	Exercise 2  Compare orthogonal collocation on finite elements with 3 nodes with a numerical integrator (e.g. ODE15s in MATLAB or ODEINT in Python). Calculate the error at each of the solution points for the equation (same as for Exercise 1):

 $5 dx/dt = -x^2 + u$ 

Orthogonal Collocation on Finite Elements

finite elements with Lobatto quadrature for the numerical solution of differential algebraic equations.

#@markdown ###Orthogonal Collocation 1

In [2]:

Discretization of a continuous time representation allow large-scale nonlinear programming (NLP) solvers to find solutions at specified intervals in a time horizon. There are many names and related techniques for obtaining mathematical relationships between derivatives and non-derivative values. Some of the terms that are relevant to this discussion include orthogonal collocation on finite elements, direct

transcription, Gauss pseudospectral method, Gaussian quadrature, Lobatto quadrature, Radau collocation, Legendre polynomials,

Chebyshev polynomials, Jacobi polynomials, Laguerre polynomials, any many more. There are many papers that discuss the details of the derivation and theory behind these methods1-5. The purpose of this section is to give a practical introduction to orthogonal collocation on