## NSAE: Classroom problem 1.1

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This document aims to solve the first Problem of the course. The statement is as follows:

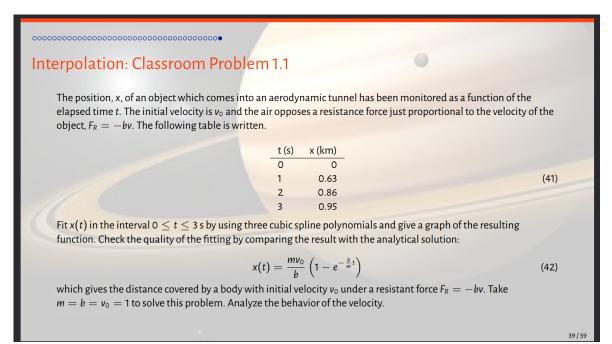


Figure 1: Problem NSAE 1.1

First we will discuss the analytical solution and it will be followed by an coded solution.

## 1 Analytical solution

Let's take a look to the data on a graph (Figure 2):

Following the procedure explained in class we can calculate the polynomial between  $t_0$  and  $t_1$  using expression 29 and 35. In this way we can find the coefficients of  $p_{0,1}$ :

$$P_{j,j+1}(t) = f_j + \left[ \frac{f_{j+1} - f_j}{h_j} - \frac{h_j p_{j+1}''}{6} - \frac{h_j p_j''}{3} \right] (t - t_j) + \frac{p_j''}{2} (t - t_j)^2 + \frac{p_{j+1}'' - p_j''}{6h_j} (t - t_j)^3$$
 (1)

In our case  $p_{0,1}$  would be calculated as:

$$p_{0,1} = 0 + \left[ \frac{0.63 - 0}{1} - \frac{1 * p_1''}{6} - \frac{1 * p_0''}{3} \right] (t - 0) + \frac{p_0''}{2} (t - 0)^2 + \frac{p_1'' - p_0''}{6 * 1} (t - 0)^3$$
 (2)

At this point we realize we need to calculate  $p_0''$  and  $p_1''$ . But as we are working with natural splines  $p_0'' = 0$ . So in order to get  $p_1''$  we will make use of expression 35 in the bibliography which states that:

$$2(h_0 + h_1)p_1'' + h_1p_2'' = \frac{6(x_2 - x_1)}{h_1} - \frac{6(x_1 - x_0)}{h_0}$$
(3)

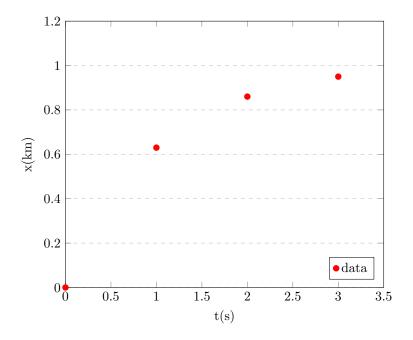


Figure 2: Data visualization

$$h_1 p_1'' + 2(h_1 + h_2) p_2'' + h_3 p_3'' = \frac{6(x_3 - x_2)}{h_2} - \frac{x_2 - x_1}{h_1}$$

$$\tag{4}$$

Where  $h_j = (t_{j+1} - t_j)$  in this case  $h_0 = h_1 = h_2 = 1$ . Resolving we have:

$$2(2)p_1'' + p_2'' = 6(0.86 - 0.63) - 6(0.63 - 0)$$
(5)

$$p_1'' + 4p_2'' + p_3'' = 6(0.95 - 0.86) - (0.86 - 0.63)$$
(6)

It results in:

$$p_1'' = -0.584$$
$$p_2'' = -0.064$$

This coupled with the natural splines condition means that we can now fully resolve equation 2 and discover the best fitting cubic spline between  $t_0$  and  $t_1$ :

$$p_{0.1} = 0.7273t - 0.0973t^3$$

with coefficients being:

$$a_0 = 0.097\overline{3}$$
  
 $b_0 = 0$   
 $c_0 = 0.0727\overline{3}$   
 $d_0 = 0$ 

Now let's look at the output of this polynomial in our case (Figure 3):

We can observe that the cubic spline fits perfectly between the interval  $0 \le t \le 1$ .

Now we could repeat the process for the other points until we have a set of 3 polynomials for each data intervals. However we could also automate this using Python and the package Scipy which provides a handy way of computing all the coefficients and providing the polynomials. We could follow the code below:

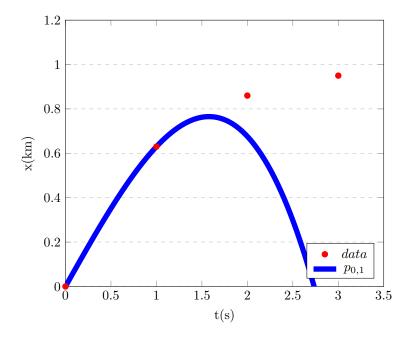


Figure 3: Data visualization

```
import numpy as np
import math
from scipy import interpolate
t=np.linspace(0,3,4,dtype=int)
x=np.array([0,0.63,0.86,0.95])

# calculate Cubic Spline using Scipy method
cs=interpolate.CubicSpline(t,xd,bc_type='natural')

#Print cs coeficients to construct polynomials (.T to transpose for easy visualitzation)
print(cs.c.T)
```

The output of this code will produce is something like this:

Which in turn can be interpreted as the following table:

Which translates to the following cubic splines:

$$p_{0,1} = 0.7273t - 0.0973t^3$$

$$p_{1,2} = 0.0866(t-1)^3 - 0.292(t-1)^2 + 0.435(t-1) + 0.630$$

$$p_{2,3} = 0.0106(t-2)^3 - 0.032(t-2)^2 + 0.111(t-2) + 0.860$$

Visually it would be translated to the following graph (Figure 4):

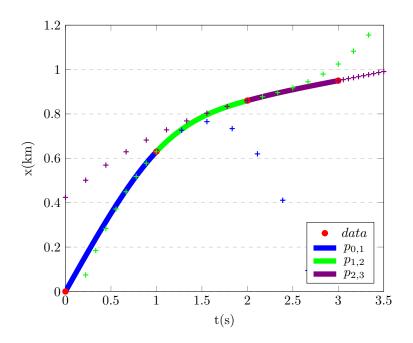


Figure 4: Representation of the splines

Furthermore we can compare the result with the analytical solution to grasp a sense of the error committed by this approximation as we can see in the figure 5:

Going one step further we can also take a look to the derivatives of our splines in figure 6 We can observe the continuity of the derivative up to the third derivation.

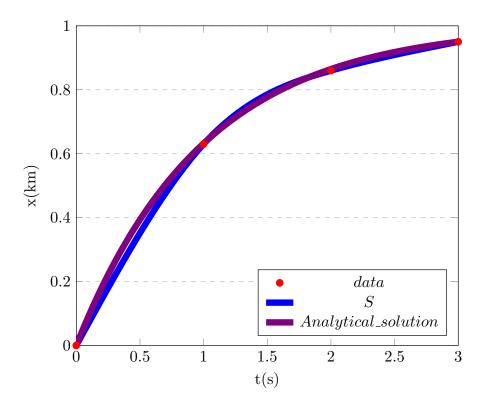


Figure 5: Comparison between analytical and approximation solutions

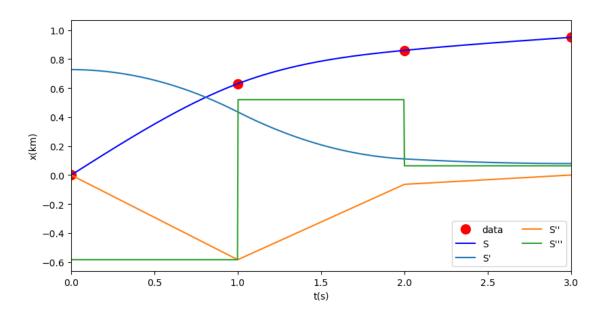


Figure 6: Spline derivatives