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import math
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

turbine_output = 9500 # kW
turbine_efficiency = 0.92 # %2 efficiency
watershed_area = 2950000000 # m^2
sec_per_day = 24 * 60 * 60
snow_amount = 200 # cm

# runoff forecast model based on model from HydroA/part6.py

t_1 = 0 # d
t_2 = 1 # d
Q_1 = 0 # m^3/s
Q_2 = 0 # initializing
A_neg = -1/3 # d

R_forecast = np.array([0, 0, 0, 0, 0, 15, 0]) # mm per hour
R_avg = np.zeros(85) # 92 days - 7 forecast days
R_avg[:24] = 1.74
R_avg[24:54] = 3
R_avg[54:] = 2.23
R_avg_sum = np.sum(R_avg)

T_forecast = np.array([14, 18, 21, 23, 24, 14, 15])
T_avg = np.zeros(85) # 92 days - 7 forecast days
T_avg[:24] = 17
T_avg[24:54] = 20
T_avg[54:] = 22
T_avg_sum = np.sum(T_avg)

# smoothing out rainfall averages, averaging over a sliding ~21 day window
R_df = pd.DataFrame({'Rainfall': R_avg})
R_df = R_df.rolling(21, min_periods=1).mean()
R_avg = R_df['Rainfall'].values

# adding back missing data from smoothing
R_avg_delta = R_avg_sum - np.sum(R_avg)
R_avg_delta_avg = np.full(len(R_avg), (R_avg_delta / len(R_avg)))
R_avg = R_avg + R_avg_delta_avg
R = np.concatenate([R_forecast, R_avg])

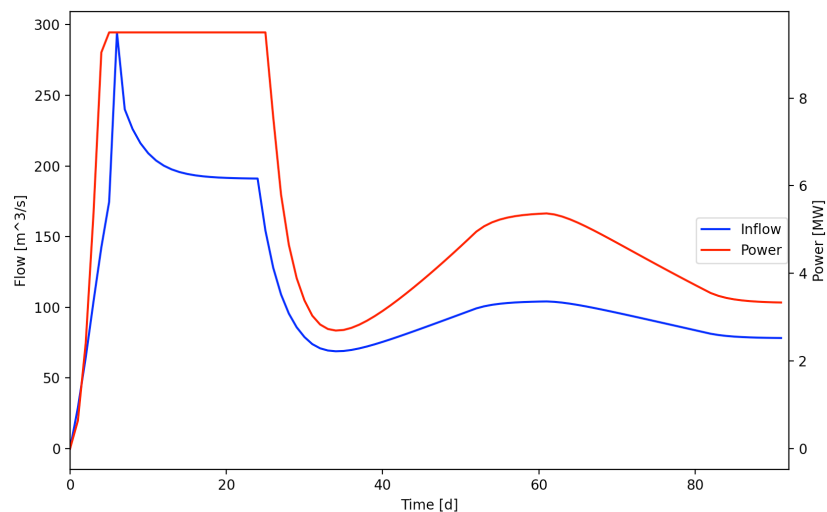
# finding bias
df = pd.read_csv('21dayforecast.csv')
df_bias = df.copy()
for day in range(1,8):
    column = "D" + str(day)
    for i in range(21):
        df_bias.iloc[i, df_bias.columns.get_loc(column)] = df.iloc[i, df.columns.get_loc(column)] - df.iloc[i, df.columns.get_loc('Observed')]

#averaging biases
df_bias = df_bias.sum(axis=0)
for i in range(1,8):
    day = "D" + str(i)
    df_bias[day] = df_bias[day] / 21

# applying bias to 7 day forecast
for day in range(1,8):
    column = "D" + str(day)
    T_forecast[day - 1] = T_forecast[day - 1] - df_bias[column]

# smoothing out temperature averages, averaging over a sliding ~21 day window
T_df = pd.DataFrame({'Temp.': T_avg})
T_df = T_df.rolling(21, min_periods=1).mean()
T_avg = T_df['Temp.'].values
# adding back missing data from smoothing
T_avg_delta = T_avg_sum - np.sum(T_avg)
T_avg_delta_avg = np.full(len(T_avg), (T_avg_delta / len(T_avg)))
T_avg = T_avg + T_avg_delta_avg
T = np.concatenate([T_forecast, T_avg])
T = T - 10 # subtracting 10 C threshold to find difference to make runoff in mm

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75 # calculate melt from 200 cm of snow
76 # remove melt amounts from T once 200 cm has been exceeded
77 cur_melt_total = 0
78 last_melt_day = len(T)
79 for i in range(len(T)):
80     cur_melt_total += T[i]
81     if (cur_melt_total >= snow_amount):
82         T[i] = T[i] - (cur_melt_total - snow_amount)
83         last_melt_day = i
84         break
85
86 T[last_melt_day:] = [0] * (len(T) - last_melt_day)
87
88 # R = R + T # adding melt and rainfall mm totals together
89
90 # converting rainfall to flow for that day
91 R = [r / 1000 for r in R] # mm to m conversion
92 R = [r / sec_per_day for r in R] # day to s conversion
93 R = [r * watershed_area for r in R] # water amount converter to volume (m^3/s)
94
95 # converting snowmelt to flow for that day
96 T = [t / 1000 for t in T] # mm to m conversion
97 T = [t / sec_per_day for t in T] # day to s conversion
98 T = [t * watershed_area * 0.5 for t in T] # water amount converter to volume (m^3/s)
99 # and accounting for 50% of area
100
101 R = np.array(R) + np.array(T) # adding melt and rainfall mm totals together
102
103 # calculate Q/ inflow
104 inflow = [0] * len(R) # m^3/s
105
106 for i in range(len(R)):
107     inflow[i] = Q_1
108     Q_2 = Q_1 * math.exp(A_neg * (t_2 - t_1)) + R[i] * (1 - math.exp(A_neg * (t_2 - t_1)))
109     Q_1 = Q_2 # ^ d in t_1 & t_2 cancel out with d^-1 in A_neg
110     t_1 = 1
111     t_2 = 1
112
113 # calculate river velocity
114 B = 2.25
115 velocity = np.array([B * q ** (1/3) for q in inflow])
116
117 #calculate power output
118 power = np.zeros(len(inflow))
119 for i in range(len(inflow)):
120     power[i] = 0.5 * turbine_efficiency * inflow[i] * (velocity[i] ** 2) / 1000 # MW
121     if (power[i] > 9.5):
122         power[i] = 9.5 # ^^ removed density as part of W to MW conversion
123
124 revenue_day = np.array([p * 1000 * 24 * 0.25 for p in power]) # daily revenue
125 revenue_total = np.sum(revenue_day)
126 print("Total revenue: " + str(revenue_total))
127
128 x = list(range(len(inflow)))
129
130 fig, host = plt.subplots(1, 1, figsize=(10,6))
131
132 par = host.twinx()
133
134 p1, = host.plot(x, inflow, label='Inflow', color='blue')
135 p2, = par.plot(x, power, label='Power', color='red')
136
137 host.set_xlim(0, len(R))
138
139 host.set_ylabel('Flow [m^3/s]')
140 host.set_xlabel('Time [d]')
141 par.set_ylabel('Power [MW]')
142
143 lines = [p1, p2]
144
145 host.legend(lines, [l.get_label() for l in lines], loc="center right", borderaxespad=0.1)
146
147 plt.subplots_adjust(right=0.85)
148
149 plt.show()
150

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I found the total revenue to be \$2952465.62.

So I decided to choose C 2.7 mill because most of the values were based off highs and it would not make sense to over estimate revenue for this scenario. Additionally we used smoother values for rainfall and temperatures if the we more erratic then we could see more scenarios where the power generated is maxed and then a quick drop do to lack of rain compared to a high intensity precipitation event. This would cause less revenue in the dryer days and wasted revenue on the high precipitation days.

The area risks of floods and avalanches/slides in the area with high intensity precipitation events.

