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# OR-541 COURSE PROJECT Chanyoung Park(G01408089),Saketh Kallepalli(G01425732)

# **Current and optimal policy**

The report outlines the recommendations for Super Chip, a Virginia-based computer chip manufacturer, regarding their production and distribution operations for the upcoming fiscal year. The company has five manufacturing facilities with varying production capacity levels, and each facility has different equipment and setup costs that impact the cost of manufacturing each of the 30 types of computer chips. Additionally, there are variations in shipping costs for distributing the computer chips to 23 sales regions across the US. The report evaluates an alternative production policy that could potentially reduce costs for Super Chip.

With its current production policy, Super Chip follows a production policy where each facility produces each of the 30 types of chips at levels that are proportional to the facility's total portion of production capacity. This means that if a facility has y% of the total production capacity across all facilities, then it currently produces y% of every chip's total demand.

After analyzing the data provided by Super Chip, it is recommended that the company should adopt a new production policy where the share of each facility for each chip is different from the current policy. The new policy is based on the optimization model that Super Chip can use to minimize their total costs. The optimization model calculates the minimum cost of producing and shipping the computer chips to each sales region by assigning the production of each chip to the facility that has the lowest cost of production for that specific chip.

The formulation of the optimization model is started by defining the decision variables. If we denote with  $x_{ijk}$  the number of chips produced at facility i (i = Alexandria(1), Richmond(2), Norfolk(3), Roanoke(4), Charlottesville(5)), for sales region j (j = 1,..23) and type of chip k (k = 1,..30), we are able to write the following constraints:

1) 
$$\sum_{j=1}^{23} \sum_{k=1}^{30} x_{ijk} \le C_i$$

Here, the total number of chips produced at facility i for all sale regions and types needs to be lower or equal to the production capacity of the very same facility  $(C_i)$ .

2) 
$$\sum_{i=1}^{5} x_{ijk} = D_{jk}$$

Here, the total number of chips produced at all facilities for a sale region j and type k needs to be equal to the demand of the very same region and type of the chip  $(D_{ik})$ .

3) 
$$x_{ijk} \ge 0$$

In the end, the production needs to be larger or equal to zero. Let's also define the objective function as:

$$f = \vec{c} * \vec{x}$$

The objective function is defined in an aggregated way, combining the cost for production and distribution in one element for each facility and sales region.

The results obtained from the optimization model show that the recommended policy can lead to cost savings for Super Chip. The cost of the current policy is \$5.6133+07 while the cost after optimization is \$4.9083e+07. This means that Super Chip could potentially save \$7.05+06 in costs by adopting the recommended policy.

# **Investment Policy**

Based on the recommended policy, Super Chip should invest in expanding the production capacity at the facility that has the lowest cost of production for the chips that would be produced with the additional equipment. According to the optimization model, the facility that should obtain the additional equipment is the one in Roanoke. This facility has the lowest cost associated with the recommended policy, with a total cost of \$9.172e+06.

Expanding the production capacity at the Roanoke facility would likely decrease the cost of production due to the acquisition of more efficient equipment. However, it is important to note that the cost of distribution would increase due to the higher number of manufactured chips. Therefore, the total impact on costs would depend on the magnitude of the cost reductions in production and the cost increases in distribution. It is important to note that the total impact on costs would depend on the specific details of the expansion and how it affects production and distribution costs.

## Increase in demand

The third strategic-level question was whether Super Chip had sufficient capacity to handle the estimated increase in demand of 10% across all sales regions for the next year. This new constraint thus can be formulated as (compared to the original optimization formulation).

$$\sum_{i=1}^{5} x_{ijk} = 1.10 * D_{jk}$$

After reformulating the optimization problem to increase the demand by 10%, the results showed that Super Chip had enough capacity to adapt to this new demand plan. The associated costs for filling new demand were \$ 4.9410e+06.

### **Decrease in Production Cost**

It is important to note that the implementation of this new manufacturing technology will have a significant impact on the overall production and distribution costs for Super Chip.

While the production costs will decrease by 15%, there will be additional costs associated with the implementation of the new technology such as training and equipment upgrades. Furthermore, the distribution costs may also be impacted due to changes in production output and shipping logistics. Therefore, it is important for Super Chip to conduct a thorough cost-benefit analysis before making a decision on the implementation of this new technology in any of its facilities. We need to formulate five different optimization problems (each associated with a 15% decrease in production cost at the respective facility). The constraints of the optimization problem are not the subject of change, so only the objective function is changed:

```
1) c_{1jkpost} = 0.85 * c_{1jkpre}, c_{ijkpost} = c_{ijkpre}, i = [2,3,4,5]
2) c_{2jkpost} = 0.85 * c_{2jkpre}, c_{ijkpost} = c_{ijkpre}, i = [1,3,4,5]
3) c_{3jkpost} = 0.85 * c_{3jkpre}, c_{ijkpost} = c_{ijkpre}, i = [1,2,4,5]
```

4) 
$$c_{4jkpost} = 0.85 * c_{4jkpre}, c_{ijkpost} = c_{ijkpre}, i = [1,2,3,5]$$
  
5)  $c_{5jkpost} = 0.85 * c_{5jkpre}, c_{ijkpost} = c_{ijkpre}, i = [1,2,3,5]$ 

Based on the results of the optimization, it is recommended that Super Chip should evaluate the new manufacturing technology in the Alexandria facility. This is because implementing the new technology at this facility results in the lowest overall cost of production. The estimated 15% reduction in production costs for all of the chips translates to significant cost savings for Super Chip, which could lead to increased profits and competitiveness in the market. However, it is important to note that there may be additional costs associated with implementing the new technology, such as training and equipment costs. These factors should be taken into consideration when making the final decision. The total cost associated with this change at Alexandria is \$4.6682e+07.

```
In [1]: import numpy as np
         import gurobipy as gp
         import pandas as pd
In [2]: # Read the data from Excel files
        data1 = np.array(pd.read excel("SuperChipData.xlsx", sheet name=0))
        data2 = np.array(pd.read excel("SuperChipData.xlsx", sheet name=1))
        data3 = np.array(pd.read excel("SuperChipData.xlsx", sheet name=2))
        data4 = np.array(pd.read excel("SuperChipData.xlsx", sheet name=3))
In [3]: # Current policy shares of each facility
        share1 = data1[0,1]/sum(data1[:,1]);
        share2 = data1[1,1]/sum(data1[:,1]);
        share3 = data1[2,1]/sum(data1[:,1]);
        share4 = data1[3,1]/sum(data1[:,1]);
         share5 = data1[4,1]/sum(data1[:,1]);
In [4]: # Define the problem data
        n = 30 * 23
        m = 5*len(data2)
In [5]: # Left-hand side inequalities
        Aineq = np.concatenate((np.hstack((np.ones((1,n)), np.zeros((1,4*n))))),
                                 np.hstack((np.zeros((1,n)), np.ones((1,n)), np.zeros((1,n)))
                                 np.hstack((np.zeros((1,2*n)), np.ones((1,n)), np.zeros
                                 np.hstack((np.zeros((1,3*n)), np.ones((1,n)), np.zeros
                                 np.hstack((np.zeros((1,4*n)), np.ones((1,n)))),
                                 -np.eye(m)), axis=0)
In [6]: # Right-hand side inequalities
        bineq = np.concatenate((data1[:,1]*1000, np.zeros((m,))), axis=0)
In [7]: # Left-hand side equalities
        Aeg = np.zeros((len(data2), m))
In [8]: for i in range(len(data2)):
             for j in range(5):
                 Aeq[i, i+j*n] = 1
In [9]: # Right-hand side equalities
        beq = data2[:,2]*1000
In [10]: # Cost vector
        c = np.zeros((m,))
         # Iterate through the cost vectors
        for k in range (1, 6):
             for i in range(23):
                 for j in range(30):
                     c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + data4[(k-1)*30 + j]
In [11]: # Cost with current policy
        COST1 = 0
         COST2 = 0
```

```
COST3 = 0
        COST4 = 0
        COST5 = 0
         # Sum up all of the elements to obtain the cost with current policy
        for k in range (1, 6):
             for i in range (1, 24):
                 for j in range (1, 31):
                     if k == 1:
                         COST1 += c[30*23*(k-1) + (i-1)*30 + j-1]*share1*data2[(i-1)*30+
                         COST2 += c[30*23*(k-1) + (i-1)*30 + j-1]*share2*data2[(i-1)*30+
                     elif k == 3:
                         COST3 += c[30*23*(k-1) + (i-1)*30 + j-1]*share3*data2[(i-1)*30+
                     elif k == 4:
                         COST4 += c[30*23*(k-1) + (i-1)*30 + j-1]*share4*data2[(i-1)*30+
                     elif k == 5:
                         COST5 += c[30*23*(k-1) + (i-1)*30 + j-1]*share5*data2[(i-1)*30+
In [12]: for i in range(5):
             if COST1 == min(COST1, COST2, COST3, COST4, COST5):
                 minindex = i
                 print ("Facility with lowest cost with current policy is Alexandria, wit
             elif COST2 == min(COST1, COST2, COST3, COST4, COST5):
                minindex = i
                 print("Facility with lowest cost with current policy is Richmond, with
             elif COST3 == min(COST1, COST2, COST3, COST4, COST5):
                minindex = i
                 print("Facility with lowest cost with current policy is Norfolk, with t
            elif COST4 == min(COST1,COST2,COST3,COST4,COST5):
                minindex = i
                 print("Facility with lowest cost with current policy is Roanoke, with t
             elif COST5 == min(COST1,COST2,COST3,COST4,COST5):
                 minindex = i
                 print("Facility with lowest cost with current policy is Charolottesvill
        Facility with lowest cost with current policy is Roanoke, with the cost of:917
        2090.517030565
        Facility with lowest cost with current policy is Roanoke, with the cost of:917
        2090.517030565
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        2090.517030565
In [13]: # Total cost of all facilities
        COST = COST1 + COST2 + COST3 + COST4 + COST5
        print("Cost with current policy is:"+str(COST))
        Cost with current policy is: 56133859.957641914
In [14]: # Create a Gurobi model
        model = gp.Model()
        Set parameter Username
        Academic license - for non-commercial use only - expires 2024-01-18
```

```
In [15]: # Define the decision variables
        x = model.addMVar(shape=m, lb=-1e30, ub=gp.GRB.INFINITY, name="x")
        # Set the objective function
In [16]:
        model.setObjective(c @ x, sense=gp.GRB.MINIMIZE)
        # Add the constraints
In [17]:
        model.addConstr(Aeq @ x == beq, name="eq")
        model.addConstr(Aineq @ x <= bineq, name="ineq")</pre>
        <MConstr (3455,) *awaiting model update*>
Out[17]:
In [18]:
        # Solve the model
        model.optimize()
        Gurobi Optimizer version 10.0.1 build v10.0.1rc0 (win64)
        CPU model: 12th Gen Intel(R) Core(TM) i5-1240P, instruction set [SSE2|AVX|AVX
        Thread count: 12 physical cores, 16 logical processors, using up to 16 threads
        Optimize a model with 4145 rows, 3450 columns and 10350 nonzeros
        Model fingerprint: 0xf6941b08
        Coefficient statistics:
          Matrix range [1e+00, 1e+00]
          Objective range [4e+01, 7e+01]
          Bounds range [0e+00, 0e+00]
          RHS range [1e+01, 3e+05]
        Presolve removed 3451 rows and 5 columns
        Presolve time: 0.02s
        Presolved: 694 rows, 3445 columns, 6890 nonzeros
        Iteration
                    Objective
                                    Primal Inf.
                                                  Dual Inf.
                                                                 Time
                    4.9059636e+07 7.737500e+03 0.000000e+00
                                                                    0s
               0
              45
                  4.9083430e+07 0.000000e+00 0.000000e+00
                                                                    0s
        Solved in 45 iterations and 0.03 seconds (0.00 work units)
        Optimal objective 4.908343040e+07
In [19]: # Get the optimal solution
        x opt1 = model.getAttr('x')
In [20]: print("Optimal solution:")
        print(x opt1)
```

Optimal solution: [0.0, 0.0, 0.0, 0.0, 0.0, 460.0, 0.0, 1750.0, 2920.0, 0.0, 2340.0, 1500.0, 131]0.0, 0.0, 730.0, 0.0, 0.0, 0.0, 280.0, 0.0, 0.0, 0.0, 0.0, 1630.0, 0.0, 0.0, 1 0, 2040.0, 2520.0, 1330.0, 0.0, 140.0, 0.0, 0.0, 0.0, 1700.0, 2970.0, 0.0, 0. 0, 0.0, 2840.0, 730.0, 0.0, 180.0, 1360.0, 1620.0, 0.0, 1220.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 470.0, 1660.0, 0.0, 2300.0, 930.0, 540.0, 0.0, 1450. 0, 0.0, 0.0, 0.0, 610.0, 0.0, 0.0, 0.0, 1470.0, 0.0, 0.0, 1860.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1590.0, 0.0, 1720.0, 2029.99999999999, 0.0, 490.0, 1660.0, 2580.0, 0.0, 260.0, 0.0, 0.0, 0.0, 2040.0, 0.0, 0.0, 0.0, 0.0, 50.0, 780.0, 0.0, 380.0, 520.0, 140.0, 0.0, 2400.0, 0.0, 0.0, 0.0, 1680.0, 0. 0, 930.0, 0.0, 2870.0, 1910.0, 0.0, 2650.0, 450.0, 1190.0, 0.0, 1060.0, 0.0, 0.0, 0.0, 140.0, 1390.0, 0.0, 0.0, 0.0, 2800.0, 0.0, 0.0, 2160.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2760.0, 1710.0, 0.0, 2810.0, 290.0, 295 0, 2020.0, 660.0, 1380.0, 0.0, 1040.0, 0.0, 0.0, 0.0, 2060.0, 0.0, 0.0, 0.0, 0, 1350.0, 1940.0, 0.0, 2490.0, 1610.0, 1150.0, 0.0, 2750.0, 0.0, 0.0, 0.0, 26 0.0, 0.0, 790.0, 0.0, 2630.0, 2520.0, 0.0, 570.0, 70.0, 890.0, 0.0, 1720.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1130.0, 300.0, 0.0, 1530.0, 1910.0, 155 0.0, 0.0, 950.0, 0.0, 0.0, 0.0, 1680.0, 0.0, 0.0, 0.0, 0.0, 1650.0, 0.0, 0.0, 0, 2110.0, 1090.0, 1750.0, 0.0, 920.0, 0.0, 0.0, 0.0, 2830.0, 0.0, 0.0, 0.0, 0.0, 2730.0, 1770.0, 0.0, 1600.0, 2390.0, 2080.0, 0.0, 2170.0, 0.0, 0.0, 0.0, 0, 0.0, 0.0, 0.0, 0.0, 0.0, 2400.0, 0.0, 290.0, 1800.0, 2980.0, 0.0, 1650.0, 0.0, 0.0, 0.0, 650.0, 0.0, 0.0, 0.0, 1520.0, 0.0, 0.0, 2230.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 590.0, 0.0, 360.0, 940.0, 0.0, 620.0, 1410.0, 17 60.0, 0.0, 590.0, 0.0, 0.0, 0.0, 310.0, 0.0, 0.0, 0.0, 0.0, 2850.0, 0.0, 0.0, 1050.0, 1350.0, 800.0, 0.0, 220.0, 0.0, 0.0, 0.0, 1670.0, 0.0, 0.0, 0.0, 0.0, 2160.0, 710.0, 0.0, 910.0, 2800.0, 130.0, 0.0, 1020.0, 0.0, 0.0, 0.0, 2710.0, 2270.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1150.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 2870.0, 0.0, 110.0, 2600.0, 0.0, 790.0, 320.0, 1320.0, 0.0, 630.0, 0. 0, 0.0, 0.0, 2040.0, 2250.0, 0.0, 0.0, 0.0, 2750.0, 0.0, 0.0, 1570.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2130.0, 0.0, 530.0, 0.0, 1010.0, 20.0, 6 0.0, 1160.0, 1810.0, 1090.0, 0.0, 2550.0, 0.0, 0.0, 0.0, 390.0, 0.0, 0.0, 0.0, 2000.0, 210.0, 0.0, 2580.0, 2850.0, 1710.0, 0.0, 750.0, 0.0, 0.0, 0.0, 630.0, 0.0, 0.0, 0.0, 0.0, 150.0, 0.0, 0.0, 2740.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 550.0, 0.0, 0.0, 390.0, 0.0, 1350.0, 2040.0, 20.0, 0.0, 2230.0, 0.0, 0.0, 0.0, 1780.0, 0.0, 0.0, 0.0, 0.0, 1730.0, 0.0, 0.0, 2530.0, 0.0, 0.0, 0.0, 0, 0.0, 940.0, 660.0, 0.0, 0.0, 1370.0, 2620.0, 560.0, 0.0, 0.0, 0.0, 0.0, 292 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1060.0, 0.0, 0.0, 0.0, 0.0, 2920.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 1660.0, 2970.0, 0.0, 0.0, 210.0, 410.0, 2720.0, 0.0, 83 0.0, 0.0, 0.0, 2620.0, 0.0, 0.0, 0.0, 0.0, 0.0, 740.0, 0.0, 0.0, 0.0, 0. 0, 2250.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1610.0, 240.0, 0.0, 0.0, 2360.0, 296 

50.0, 0.0, 0.0, 0.0, 1480.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1050.0, 1830.0, 0. 0, 0.0, 2280.0, 1000.0, 1640.0, 0.0, 0.0, 0.0, 0.0, 940.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 800.0, 0.0, 0.0, 0.0, 0.0, 1480.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 257 0.0, 790.0, 0.0, 0.0, 2690.0, 1180.0, 1910.0, 0.0, 0.0, 0.0, 0.0, 2270.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 980.0, 0.0, 0.0, 0.0, 810.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2430.0, 1090.0, 0.0, 0.0, 1190.0, 1310.0, 2870.0, 470.0, 0.0, 0.0, 0.0, 1170.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1250.0, 0.0, 0.0, 0.0, 0.0, 1020.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2920.0, 160.0, 0.0, 0.0, 2180.0, 2430.0, 2790.0, 0.0, 0.0, 0.0, 0.0, 1320.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1990.0, 1070.0, 0.0, 0.0, 0.0, 2330.0, 0.0, 0.0, 0.0, 0.0, 0.0, 550.0, 1580.0, 0.0, 0.0, 1030. 0, 2060.0, 470.0, 0.0, 630.0, 0.0, 0.0, 1400.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 50.0, 0.0, 0.0, 0.0, 0.0, 1300.0, 0.0, 0.0, 0.0, 0.0, 0.0, 590.0, 1310.0, 0.0, 0.0, 180.0, 560.0, 1430.0, 2430.0, 310.0, 0.0, 0.0, 1750.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 2720.0, 0.0, 0.0, 0.0, 320.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 640.0, 2960.0, 0.0, 0.0, 2480.0, 810.0, 810.0, 2950.0, 0.0, 0.0, 0.0, 20 0, 0.0, 0.0, 0.0, 0.0, 1470.0, 2029.99999999999, 0.0, 0.0, 500.0, 1910.0, 20 90.0, 0.0, 0.0, 0.0, 0.0, 2950.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 740.0, 2000.0, 0.0, 0.0, 0.0, 150.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2780.0, 2230.0, 0.0, 0.0, 890.0, 2860.0, 2870.0, 0.0, 0.0, 0.0, 0.0, 510.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0. 0, 2340.0, 0.0, 0.0, 0.0, 0.0, 1070.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1580.0, 2 550.0, 0.0, 0.0, 2330.0, 1030.0, 450.0, 0.0, 0.0, 0.0, 0.0, 520.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2420.0, 0.0, 0.0, 0.0, 0.0, 2140.0, 0.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 1290.0, 2029.99999999999, 0.0, 0.0, 2490.0, 550.0, 600.0, 370.0, 0. 0, 0.0, 0.0, 2790.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2170.0, 2160.0, 0.0, 0.0, 0.0, 750.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1520.0, 1980.0, 0.0, 0.0, 1920.0, 29 00.0, 840.0, 0.0, 1040.0, 0.0, 0.0, 2580.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 940. 0, 0.0, 0.0, 0.0, 0.0, 2640.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 680.0, 1090.0, 0. 0, 0.0, 2990.0, 290.0, 340.0, 0.0, 1860.0, 0.0, 0.0, 1930.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 2780.0, 0.0, 0.0, 0.0, 0.0, 2140.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2510.0, 1810.0, 0.0, 0.0, 1400.0, 2430.0, 990.0, 0.0, 0.0, 0.0, 0.0, 1730.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1920.0, 0.0, 0.0, 0.0, 0.0, 2610.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 1210.0, 780.0, 0.0, 0.0, 840.0, 2740.0, 1360.0, 720.0, 0.0, 0.0, 0.0, 280.0, 0.0, 0.0, 0.0, 0.0, 0.0, 580.0, 0.0, 0.0, 0.0, 0.0, 138 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1380.0, 370.0, 0.0, 0.0, 2090.0, 2980.0, 17 90.0, 0.0, 1200.0, 0.0, 0.0, 2170.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 350.0, 0.0, 0.0, 0.0, 0.0, 790.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2970.0, 2760.0, 0.0, 0.0, 960.0, 0.0, 0.0, 280.0, 880.0, 1540.0, 1290.0, 170.0, 0.0, 0.0, 420.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 1470.0, 1690.0, 0.0, 0.0, 0.0, 590.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 620.0, 1980.0, 0.0, 0.0, 1570.0, 1280.0, 2100.0, 0.0, 0.0, 0.0, 0.0, 2210.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1810.0, 0.0, 0.0, 0.0, 0.0, 130.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1340.0, 1860.0, 0.0, 0.0, 2330.0, 1770.0, 230.0, 0.0, 2890.0, 0.0, 0.0, 2550.0, 0.0, 0.0, 0.0, 2170.0, 2820.0, 870.0, 0.0, 0.0, 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 690.0, 700.0, 0.0, 1030.0, 2050.0, 80.0, 0.0, 2930.0, 190.0, 1660.0, 0.0, 0.0, 1710.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0. 0.0, 1780.0, 0.0, 900.0, 2140.0, 1370.0, 0.0, 0.0, 180.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1610.0, 2190.0, 0.0, 1430.0, 1730.0, 2990.0, 0.0, 0.0, 1390.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1520.0, 700.0, 0.0, 2670.0, 1130.0, 550.0, 0.0, 0.0, 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2720.0, 1010.0, 0.0, 2930.0, 2280.0, 119

1670.0, 2910.0, 0.0, 1440.0, 660.0, 430.0, 0.0, 0.0, 430.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 1660.0, 1820.0, 0.0, 880.0, 330.0, 1880.0, 0.0, 0.0, 430.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2670.0, 2820.0, 0.0, 1710.0, 1130.0, 2050.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2310.0, 230.0, 0.0, 2920.0, 2690.0, 246 0.0, 0.0, 1140.0, 2880.0, 1060.0, 0.0, 0.0, 1750.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2490.0, 1850.0, 0.0, 2310.0, 2370.0, 1240.0, 0.0, 0.0, 2100.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 650.0, 870.0, 0.0, 2280.0, 2780.0, 1630.0, 0.0, 0.0, 1850. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 90.0, 1270.0, 0.0, 1510.0, 520.0, 100.0, 0.0, 0.0, 0.0, 1520.0, 320.0, 0.0, 2600.0, 1780.0, 1440.0, 0.0, 0.0, 1730.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1570.0, 2870.0, 1180.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,  $0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 1580.0,\ 0.0,\ 0.0,$ 0, 0.0, 0.0, 0.0, 210.0, 2250.0, 0.0, 0.0, 0.0, 0.0, 760.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 150.0, 1970.0, 0.0, 0.0, 0.0, 0.0, 2460.0, 0.0, 0.0, 0. 70.0, 0.0, 0.0, 0.0, 0.0, 1780.0, 1350.0, 0.0, 0.0, 0.0, 0.0, 2370.0, 0.0, 0. 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1210.0, 1670.0, 0.0, 0.0, 0.0, 0.0, 1720.0, 0.0, 0.0, 0.0, 630.0, 0.0, 0.0, 0.0, 0.0, 0.0, 360.0, 0.0, 0.0, 0.0, 0.0, 1370.0, 0, 0.0, 0.0, 0.0, 890.0, 0.0, 0.0, 0.0, 1350.0, 1280.0, 0.0, 0.0, 0.0, 0. 0.0, 0.0, 0.0, 0.0, 2500.0, 0.0, 0.0, 0.0, 0.0, 1190.0, 660.0, 0.0, 0.0, 0.0, 

0.0, 0.0, 0.0, 0.0, 0.0, 290.0, 0.0, 0.0, 0.0, 1290.0, 1510.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1300.0, 0.0, 0.0, 0.0, 0.0, 240.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 1270.0, 0.0, 0.0, 0.0, 0.0, 0.0, 540.0, 0.0, 0.0, 0.0, 0.0,  $0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 910.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 1710.0,\ 0.$ 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 850.0, 0.0, 0.0, 0.0, 0.0, 1220.0, 0, 2780.0, 0.0, 0.0, 0.0, 0.0, 1470.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1280.0,  $0.0,\ 0.0,\ 2730.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,$ 0.0, 1790.0, 1900.0, 0.0, 0.0, 0.0, 0.0, 2930.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0, 0.0, 0.0, 0.0, 0.0, 0.0, 2029.99999999999, 0.0, 0.0, 0.0, 0.0, 0.0, 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 750.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 

```
In [21]: # Preallocation
      aux = 0
      share = np.zeros((5, 30))
In [22]: # Cost of the new policy
      print('Cost of the new policy is:')
      print(np.dot(c, x opt1))
      Cost of the new policy is:
      49083430.4
In [23]: print("The potential save if adopting new policy:")
      print(COST-np.matmul(np.transpose(c),x opt1))
      The potential save if adopting new policy:
      7050429.557641916
In [24]: | # Finding the share of each facility for each type of chip
      for k in range(1, 6):
         for i in range(1, 31):
           for j in range(i, len(data2)+1, 30):
              share[k-1, i-1] += x_{opt1}[(k-1)*30*23 + j-1]
              aux += data2[j-1, 2]*1000
           share [k-1, i-1] /= aux
           aux = 0
In [25]: # Cost per facility with optimized policy
      costperfac = np.zeros(5)
In [26]: for i in range(1, 6):
        costperfac[i-1] = np.dot(c[(i-1)*30*23:i*30*23], x opt1[(i-1)*30*23:i*30*23])
In [27]: # Solve for 10% increase in production
      # Right-hand side equalities
      beq = data2[:,2]*1000*1.10
In [28]: # Cost vector
      c = np.zeros((m,))
In [29]: # Iterate through the cost vectors
      for k in range (1, 6):
        for i in range(23):
           for j in range(30):
              c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + data4[(k-1)*30 + j]
In [30]: # Create a Gurobi model
      model = gp.Model()
```

```
In [31]: # Define the decision variables
        x = model.addMVar(shape=m, lb=-1e30, ub=gp.GRB.INFINITY, name="x")
        # Set the objective function
In [32]:
        model.setObjective(c @ x, sense=gp.GRB.MINIMIZE)
        model.addConstr(Aeq @ x == beq, name="eq")
In [33]:
        model.addConstr(Aineq @ x <= bineq, name="ineq")</pre>
        <MConstr (3455,) *awaiting model update*>
Out[33]:
In [34]: # Solve the model
        model.optimize()
        Gurobi Optimizer version 10.0.1 build v10.0.1rc0 (win64)
        CPU model: 12th Gen Intel(R) Core(TM) i5-1240P, instruction set [SSE2|AVX|AVX
        2]
        Thread count: 12 physical cores, 16 logical processors, using up to 16 threads
        Optimize a model with 4145 rows, 3450 columns and 10350 nonzeros
        Model fingerprint: 0x93ba71f1
        Coefficient statistics:
          Matrix range [1e+00, 1e+00]
          Objective range [4e+01, 7e+01]
          Bounds range [0e+00, 0e+00]
RHS range [1e+01, 3e+05]
        Presolve removed 3451 rows and 5 columns
        Presolve time: 0.01s
        Presolved: 694 rows, 3445 columns, 6890 nonzeros
                                                   Dual Inf.
        Iteration
                    Objective
                                    Primal Inf.
                                                                   Time
                    5.3965600e+07 1.241125e+04 0.000000e+00
                                                                      0s
                    5.4024420e+07 0.000000e+00 0.000000e+00
              81
                                                                      0s
        Solved in 81 iterations and 0.02 seconds (0.00 work units)
        Optimal objective 5.402442027e+07
In [35]: # Get the optimal solution for 10% increase
        x opt2 = model.getAttr('x')
In [36]: print("Optimal solution for 10% increase in production:")
        print(x opt2)
```

Optimal solution for 10% increase in production:  $[0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 506.0000000000006,\ 0.0,\ 1925.0000000000002,\ 3212.00$ 0000000005, 0.0, 2574.0, 1650.000000000002, 1441.00000000002, 0.0, 803.000 0000000001, 0.0, 0.0, 0.0, 308.0, 0.0, 0.0, 0.0, 1793.00000000002, 0.0,  $0.0,\ 1738.0000000000002,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 3234.00000000$ 00005, 0.0, 1331.0, 1353.0, 0.0, 2244.0, 2772.0, 1463.000000000002, 0.0, 154. 0, 0.0, 0.0, 1870.000000000002, 3267.00000000005, 0.0, 0.0, 0.0, 286. 00000000001, 0.0, 0.0, 803.000000000001, 0.0, 198.000000000003, 1496.00000 00000002, 1782.000000000002, 0.0, 1342.0, 0.0, 0.0, 0.0, 1144.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 517.0, 1826.000000000002, 0.0, 2530.0, 1023.00000000001, 594.0, 0.0, 1595.0000000000002, 0.0, 0.0, 0.0, 671.0, 0.0, 0.0, 0.0, 0.0, 161 0.0, 0.0, 1749.0000000000002, 0.0, 1892.000000000002, 2233.0, 0.0, 539.0, 182 6.000000000002, 2838.00000000005, 0.0, 286.0, 0.0, 0.0, 0.0, 2244.0, 0.0, 0.0, 0.0, 0.0, 836.000000000001, 0.0, 0.0, 1034.0, 0.0, 0.0, 0.0, 0.0, 0.0,  $0.0,\ 0.0,\ 0.0,\ 1441.0000000000002,\ 0.0,\ 275.0,\ 858.000000000001,\ 0.0,\ 418.000$ 0000000006, 572.0, 154.0, 0.0, 2640.0, 0.0, 0.0, 0.0, 1848.000000000002, 0. 0, 1023.000000000001, 0.0, 3157.00000000005, 2101.0, 0.0, 2915.00000000000 5, 495.0000000000006, 1309.0, 0.0, 1166.0, 0.0, 0.0, 0.0, 154.0, 0.0, 0.0, 0. 0, 0.0, 3080.000000000005, 0.0, 0.0, 2376.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 1177.0, 0.0, 3036.000000000005, 1881.000000000002, 0.0, 3091.000000 000005, 319.0, 3245.000000000005, 0.0, 1914.00000000002, 0.0, 0.0, 0.0, 88 0.00000000001, 0.0, 0.0, 0.0, 0.0, 3135.00000000005, 0.0, 0.0, 1859.00000 0, 2222.0, 726.000000000001, 1518.00000000002, 0.0, 1144.0, 0.0, 0.0, 0.0, 2266.0, 0.0, 0.0, 0.0, 0.0, 2673.0, 0.0, 0.0, 1793.0000000000002, 0.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 1034.0, 0.0, 0.0, 2134.0, 0.0, 2739.0, 1771.000000 0000002, 1265.0, 0.0, 3025.000000000005, 0.0, 0.0, 0.0, 2937.00000000005, 0.0, 0.0, 0.0, 0.0, 3245.000000000005, 0.0, 0.0, 2057.0, 0.0, 0.0, 0.0, 0.0,  $0.0,\ 0.0,\ 0.0,\ 0.0,\ 869.00000000001,\ 0.0,\ 2893.00000000005,\ 2772.0,\ 0.0,\ 6$ 27.0, 77.0, 979.000000000001, 0.0, 1892.000000000002, 0.0, 0.0, 0.0, 605.0, 0.0, 0.0, 0.0, 0.0, 737.000000000001, 0.0, 0.0, 3223.00000000005, 0.0, 0.0, 002, 2101.0, 1705.000000000002, 0.0, 1045.0, 0.0, 0.0, 0.0, 1848.00000000000 2, 0.0, 0.0, 0.0, 0.0, 1815.000000000002, 0.0, 0.0, 462.0000000000006, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 528.0, 0.0, 0.0, 1573.000000000002, 0.0, 2 321.0, 1199.0, 1925.0000000000002, 0.0, 1012.00000000001, 0.0, 0.0, 0.0, 311 3.000000000005, 0.0, 0.0, 0.0, 0.0, 209.00000000003, 0.0, 0.0, 2695.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 528.0, 0.0, 3003.000000000005, 1947.000 0000000002, 0.0, 1760.000000000002, 2629.0, 2288.0, 0.0, 2387.0, 0.0, 0.0, 0. 0, 1155.0, 0.0, 0.0, 0.0, 0.0, 407.000000000006, 0.0, 0.0, 121.000000000000 0, 0.0, 319.0, 1980.0000000000002, 3278.00000000005, 0.0, 1815.00000000000 2, 0.0, 0.0, 0.0, 715.000000000001, 0.0, 0.0, 0.0, 0.0, 1672.000000000002, 0000000006, 1034.0, 0.0, 682.0, 1551.000000000002, 1936.000000000002, 0.0, 6 49.0, 0.0, 0.0, 0.0, 341.0, 0.0, 0.0, 0.0, 3135.00000000005, 0.0, 0.0, 1628.0000000000002, 0.0, 1155.0, 1485.000000000002, 880.00000000001, 0.0, 2 42.000000000003, 0.0, 0.0, 0.0, 1837.000000000002, 0.0, 0.0, 0.0, 0.0, 217 002, 0.0, 0.0, 781.000000000001, 0.0, 1001.00000000001, 3080.00000000005, 143.0, 0.0, 1122.0, 0.0, 0.0, 0.0, 2981.00000000005, 0.0, 0.0, 0.0, 0.0, 79 7.000000000005, 0.0, 121.000000000001, 2860.0000000005, 0.0, 869.000000 000001, 352.0, 1452.0000000000002, 0.0, 693.0, 0.0, 0.0, 0.0, 2244.0, 0.0, 0. 0, 0.0, 0.0, 3025.000000000005, 0.0, 0.0, 1727.000000000002, 0.0, 0.0, 0.0,

0.0, 0.0, 0.0, 0.0, 0.0, 2343.0, 0.0, 583.0, 0.0, 1111.0, 22.0, 715.00000 00000001, 0.0, 2651.0, 0.0, 0.0, 0.0, 1386.0, 0.0, 0.0, 0.0, 0.0, 22.0, 0.0, 1452.000000000002, 2728.0, 0.0, 1276.0, 1991.00000000002, 1199.0, 0.0, 280 1.0000000000003, 0.0, 2838.000000000005, 3135.00000000005, 1881.000000000 002, 0.0, 825.000000000001, 0.0, 0.0, 0.0, 693.0, 0.0, 0.0, 0.0, 0.0, 165.0, 3.0, 0.0, 0.0, 0.0, 1958.000000000002, 0.0, 0.0, 0.0, 0.0, 1903.0000000000 2, 0.0, 0.0, 2783.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2893.00000000005, 0. 01, 0.0, 0.0, 1507.000000000002, 2882.00000000005, 616.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1166.0, 0.0, 0.0, 0.0, 0.0, 3212.0000000 000005, 0.0, 0.0, 0.0, 0.0, 0.0, 1826.000000000002, 3267.0000000005, 0.0, 0.0, 231.00000000000003, 451.000000000006, 2992.00000000005, 0.0, 91 14.00000000001, 0.0, 0.0, 0.0, 0.0, 2475.0, 0.0, 0.0, 0.0, 0.0, 0.0, 17 71.000000000002, 264.0, 0.0, 0.0, 2596.0, 3256.00000000005, 286.0, 0.0, 0. 000000000002, 0.0, 0.0, 2508.0, 1100.0, 1804.000000000002, 0.0, 0.0, 0.0, 0. 0, 1034.0, 0.0, 0.0, 0.0, 0.0, 0.0, 880.0000000001, 0.0, 0.0, 0.0, 0. 00000000001, 0.0, 0.0, 2959.000000000005, 1298.0, 2101.0, 0.0, 0.0, 0.0, 0. 0, 2497.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1078.0, 0.0, 0.0, 0.0, 891.00000 1.000000000002, 3157.000000000005, 517.0, 0.0, 0.0, 0.0, 1287.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1375.0, 0.0, 0.0, 0.0, 1122.0, 0.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 3212.000000000005, 176.0, 0.0, 0.0, 2398.0, 2673.0, 3069.0000000000 0, 0.0, 0.0, 0.0, 0.0, 2563.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 605.0, 1738.00000 00000002, 0.0, 0.0, 1133.0, 2266.0, 517.0, 0.0, 0.0, 0.0, 0.0, 1394.000000000 0.0, 198.0000000000000, 616.0, 1573.000000000002, 0.0, 0.0, 0.0, 0.0, 1925.0 0.0, 352.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 704.0, 3256.00000000005, 0.0, 0.0, 2728.0, 891.000000000001, 891.00000000001, 0.0, 0.0, 0.0, 0.0, 220.0000000 000003, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2420.0, 0.0, 0.0, 0.0, 0.0, 1496.0000000 000002, 0.0, 0.0, 0.0, 0.0, 0.0, 1617.00000000002, 2233.0, 0.0, 0.0, 55 0.0, 2101.0, 2299.0, 0.0, 0.0, 0.0, 0.0, 3245.00000000005, 0.0, 0.0, 0.0, 0. 0, 0.0, 0.0, 814.000000000001, 0.0, 0.0, 0.0, 165.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 3058.000000000005, 2453.0, 0.0, 0.0, 979.00000000001, 3146.00000 0.0, 2574.0, 0.0, 0.0, 0.0, 0.0, 1177.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1738.00 00000000002, 2805.0, 0.0, 0.0, 2563.0, 1133.0, 495.0000000000006, 0.0, 0.0, 0.0, 0.0, 572.0, 0.0, 0.0, 0.0, 0.0, 0.0, 2662.0, 0.0, 0.0, 0.0, 0.0, 235 4.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1419.000000000002, 2233.0, 0.0, 0.0, 2739. 0, 1932.000000000007, 0.0, 0.0, 0.0, 825.00000000001, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1672.0000000000002, 2178.0, 0.0, 0.0, 2112.0, 3190.00000000005, 92 4.00000000001, 0.0, 0.0, 0.0, 0.0, 2838.00000000005, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1034.0, 0.0, 0.0, 0.0, 0.0, 2904.00000000005, 0.0, 0.0, 0.0, 0.0, 0.0, 748.000000000001, 1199.0, 0.0, 0.0, 3289.00000000005, 319.0, 374. 000000000000, 0.0, 0.0, 0.0, 0.0, 2123.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 305 8.000000000005, 0.0, 0.0, 0.0, 0.0, 2354.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 276 1.0, 1991.000000000000, 0.0, 0.0, 1540.00000000000, 2673.0, 1089.0, 0.0, 0. 

0000000001, 0.0, 0.0, 924.000000000001, 3014.00000000005, 1496.00000000000 2, 0.0, 0.0, 0.0, 0.0, 308.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 638.0, 0.0, 0.0, 2, 407.0000000000006, 0.0, 0.0, 2299.0, 3278.00000000005, 1969.0000000000 2, 0.0, 0.0, 0.0, 0.0, 2387.0, 0.0, 0.0, 0.0, 0.0, 0.0, 385.000000000000 00000000005, 3036.00000000005, 0.0, 0.0, 1540.00000000002, 1694.00000000 56.0, 0.0, 0.0, 308.0, 968.00000000001, 1694.00000000002, 1419.0000000000 000000002, 0.0, 0.0, 0.0, 0.0, 649.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 682.0, 217 8.0, 0.0, 0.0, 1727.0000000000002, 1408.0, 2310.0, 0.0, 0.0, 0.0, 0.0, 2431.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1991.000000000002, 0.0, 0.0, 0.0, 0.0, 143.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1474.00000000002, 2046.00000000002, 0.0, 0. 0, 2563.0, 1947.0000000000002, 253.000000000003, 0.0, 849.999999999994, 0. 0, 0.0, 2805.0, 0.0, 0.0, 0.0, 2387.0, 3102.00000000005, 957.00000000001, 000005, 759.000000000001, 770.00000000001, 0.0, 1133.0, 2255.0, 88.0, 0.0, 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1562.000000000002, 2013.000000000 002, 0.0, 1452.0000000000002, 1661.000000000002, 3212.00000000005, 0.0, 0. 00002, 99.000000000001, 0.0, 3223.0000000005, 209.00000000003, 1826.00 0.0, 1815.0000000000002, 1958.000000000002, 0.0, 990.000000000001, 2354.0, 1 0, 0.0, 0.0, 1771.000000000002, 2409.0, 0.0, 1573.000000000002, 1903.000000 000002, 3289.000000000005, 0.0, 0.0, 1529.000000000002, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1672.0000000000002, 770.00000000001, 0.0, 2937.00000000005, 124 5, 1111.0, 0.0, 3223.000000000005, 2508.0, 1309.0, 0.0, 0.0, 2981.0000000000 451.00000000000006, 0.0, 1606.0000000000002, 3234.00000000005, 2970.0000000 0.0, 0.0, 1441.0000000000002, 737.00000000001, 176.0, 0.0, 0.0, 44.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1837.000000000002, 3201.00000000005, 0.0, 1584.000 0000000002, 726.000000000001, 473.000000000006, 0.0, 0.0, 473.00000000000 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1826.000000000002, 2002.00000000002, 0.0, 968.00000000001, 363.000000000000, 2068.0, 0.0, 0.0, 473.00000000000, 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 561.0, 2937.00000000005, 3102.0000000 00005, 0.0, 1881.000000000002, 1243.0, 2255.0, 0.0, 0.0, 660.0, 0.0, 0.0, 0. 0.0, 0.0, 0.0, 2541.0, 253.0000000000003, 0.0, 3212.000000000005, 2959.00000 0.0, 3069.000000000005, 2222.0, 2563.0, 0.0, 1441.000000000002, 2772.0, 946. 

005, 979.00000000001, 0.0, 1254.0, 3168.00000000005, 1166.0, 0.0, 0.0, 192  $0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 2739.0,\ 2035.00000$ 00000002, 0.0, 2541.0, 2607.0, 1364.0, 0.0, 0.0, 2310.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 715.000000000001, 957.00000000001, 0.0, 2508.0, 3058.00 0000000005, 1793.00000000002, 0.0, 0.0, 2035.00000000002, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 99.0000000000001, 1397.0, 0.0, 1661.000000000002, 572.0, 110. 12.000000000005, 2024.000000000002, 0.0, 1408.0, 2365.0, 1848.000000000002, 0000003, 1804.0000000000002, 781.00000000001, 0.0, 2937.00000000005, 2992. 00000000005, 3003.00000000005, 0.0, 0.0, 2871.00000000005, 0.0, 0.0, 0. 0.0, 0.0, 0.0, 0.0, 0.0, 275.0, 1705.00000000002, 0.0, 1243.0, 2860.000  $0.0,\ 0.0,\ 0.0,\ 1672.000000000002,\ 352.0,\ 0.0,\ 2860.000000000005,\ 1958.00000$ 0000002, 1584.0000000000002, 0.0, 0.0, 1903.000000000002, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1727.000000000002, 3157.00000000005, 1298.0, 0.0, 0.0, 0, 1738.000000000002, 0.0, 0.0, 0.0, 572.0, 726.00000000001, 0.0, 0.0, 000002, 0.0, 0.0, 0.0, 0.0, 2046.000000000002, 1397.0, 0.0, 0.0, 0.0, 0.0, 9 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1936.000000000002, 0.0, 0.0, 0.0, 0.0, 231.0000 0000000003, 2475.0, 0.0, 0.0, 0.0, 0.0, 836.00000000001, 0.0, 0.0, 0.0, 0.0, 0000000002, 0.0, 0.0, 0.0, 0.0, 165.0, 2167.0, 0.0, 0.0, 0.0, 0.0, 2706.0, 0. 0.0, 0.0, 77.0, 0.0, 0.0, 0.0, 1958.00000000002, 1485.00000000002, 0. 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1529.000000000002, 0.0, 0.0, 0.0, 0.0, 1331.0, 1837.000000000002, 0.0, 0.0, 0.0, 1892.000000000002, 0.0, 0.0, 0, 2761.0, 0.0, 0.0, 0.0, 0.0, 693.0, 990.00000000001, 0.0, 0.0, 0.0, 0.0, 1 0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 693.0, 0.0, 0.0, 0.0, 0.0, 341.0, 396.0000000 0.0, 0.0, 0.0, 0.0, 0.0, 2937.00000000005, 1804.00000000002, 0.0, 0.0, 0. 0.0, 0.0, 0.0, 1309.0, 726.000000000001, 0.0, 0.0, 0.0, 0.0, 1276.0, 0.0, 0. 0.0, 0.0, 0.0, 0.0, 319.0, 0.0, 0.0, 0.0, 1419.00000000002, 1661.000000 0.0, 0.0, 264.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1397.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0. 

00001, 0.0, 0.0, 0.0, 0.0, 1144.0, 1881.000000000002, 0.0, 0.0, 0.0, 0.0, 303 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 484.0000000000006, 0.0, 0.0, 0.0, 0.0, 2046.000 0000000002, 231.0000000000003, 0.0, 0.0, 0.0, 0.0, 671.0, 0.0, 0.0, 0.0, 0.0,  $0.0,\ 0.0,\ 2420.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 935.0$ 00000000001, 0.0, 0.0, 0.0, 0.0, 1342.0, 440.000000000006, 0.0, 0.0, 0.0, 00000002, 1287.0, 0.0, 0.0, 0.0, 0.0, 2651.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0. 0, 0.0, 1320.0, 3058.000000000005, 0.0, 0.0, 0.0, 0.0, 1617.000000000002, 0. 0, 0.0, 0.0, 2552.0, 0.0, 0.0, 0.0, 3113.00000000005, 957.00000000000 0.0, 2035.0000000000002, 0.0, 0.0, 0.0, 0.0, 1969.000000000002, 2090.0, 0.0,  $0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 0.0,\ 825.000000000001,\ 0.0,\ 0.0,$ 

```
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 143.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
      0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
In [37]: | print("The associated costs for filling new demand is:")
      print(np.matmul(np.transpose(c),x opt2)-np.matmul(np.transpose(c),x opt1))
      The associated costs for filling new demand is:
      4940989.870000012
In [38]: # Right-hand side equalities
      beq = data2[:,2]*1000
In [39]: # Cost vector - here m instead of 5*23*30
      c = np.zeros((m,));
      # Preallocation of the solution vector for a change in
      x = np.zeros((3450,5));
      cost = np.zeros((1,5));
In [40]: # Iterate through the cost vectors
      for k in range (1, 6):
         for i in range(23):
            for j in range(30):
               if k == 1:
                 c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + 0.85*data4[(k-1)*n + i*30 + j]
               else:
                 c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + data4[(k-1)*30
In [41]: # Create a Gurobi model
      model = gp.Model()
In [42]:  # Define the decision variables
      x0 = model.addMVar(shape=m, lb=-1e30, ub=gp.GRB.INFINITY, name="x")
In [43]: # Set the objective function
      model.setObjective(c @ x0, sense=gp.GRB.MINIMIZE)
In [44]: # Add the constraints
      model.addConstr(Aeq @ x0 == beq, name="eq")
      model.addConstr(Aineg @ x0 <= bineg, name="ineg")</pre>
      <MConstr (3455,) *awaiting model update*>
Out[44]:
      # Solve the model
In [45]:
      model.optimize()
```

```
Gurobi Optimizer version 10.0.1 build v10.0.1rc0 (win64)
        CPU model: 12th Gen Intel(R) Core(TM) i5-1240P, instruction set [SSE2|AVX|AVX
         2]
         Thread count: 12 physical cores, 16 logical processors, using up to 16 threads
         Optimize a model with 4145 rows, 3450 columns and 10350 nonzeros
        Model fingerprint: 0x1d262bce
        Coefficient statistics:
          Matrix range [1e+00, 1e+00]
          Objective range [4e+01, 7e+01]
          Bounds range [0e+00, 0e+00]
RHS range [1e+01, 3e+05]
          RHS range
                            [1e+01, 3e+05]
         Presolve removed 3451 rows and 5 columns
         Presolve time: 0.01s
         Presolved: 694 rows, 3445 columns, 6890 nonzeros
        Iteration Objective
                                     Primal Inf.
                                                    Dual Inf.
                                                                   Time
                    4.5692423e+07 3.876500e+04
                                                    0.000000e+00
                                                                       0s
              221
                    4.6682423e+07 0.000000e+00 0.000000e+00
                                                                       0s
         Solved in 221 iterations and 0.02 seconds (0.00 work units)
         Optimal objective 4.668242343e+07
In [46]: # Get the optimal solution
         x[:, 0] = model.getAttr('x')
         cost[:, 0] = np.matmul(np.transpose(c), x[:, 0])
In [47]: # Iterate through the cost vectors
         for k in range (1, 6):
            for i in range(23):
                 for j in range (30):
                     if k == 2:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + 0.85*data4[(k-1)*n + i*30 + j]
                     else:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + data4[(k-1)*30
In [48]: # Create a Gurobi model
         model = gp.Model()
In [49]: # Define the decision variables
         x1 = model.addMVar(shape=m, lb=-1e30, ub=gp.GRB.INFINITY, name="x")
In [50]: # Set the objective function
         model.setObjective(c @ x1, sense=gp.GRB.MINIMIZE)
In [51]: # Add the constraints
         model.addConstr(Aeq @ x1 == beq, name="eq")
         model.addConstr(Aineq @ x1 <= bineq, name="ineq")</pre>
        <MConstr (3455,) *awaiting model update*>
Out[51]:
In [52]: | # Solve the model
         model.optimize()
```

```
Gurobi Optimizer version 10.0.1 build v10.0.1rc0 (win64)
        CPU model: 12th Gen Intel(R) Core(TM) i5-1240P, instruction set [SSE2|AVX|AVX
         2]
         Thread count: 12 physical cores, 16 logical processors, using up to 16 threads
         Optimize a model with 4145 rows, 3450 columns and 10350 nonzeros
        Model fingerprint: 0x676b3443
        Coefficient statistics:
          Matrix range [1e+00, 1e+00]
          Objective range [8e+01, 1e+02]
          Bounds range [0e+00, 0e+00]
RHS range [1e+01, 3e+05]
          RHS range
                            [1e+01, 3e+05]
         Presolve removed 3451 rows and 5 columns
         Presolve time: 0.01s
         Presolved: 694 rows, 3445 columns, 6890 nonzeros
        Iteration Objective
                                     Primal Inf.
                                                    Dual Inf.
                                                                   Time
                     9.2775624e+07 3.002625e+04
                                                    0.000000e+00
                                                                       0s
                    9.3699580e+07 0.000000e+00 0.000000e+00
              205
                                                                       0s
         Solved in 205 iterations and 0.01 seconds (0.01 work units)
         Optimal objective 9.369958032e+07
In [53]: # Get the optimal solution
         x[:, 1] = model.getAttr('x')
         cost[:, 1] = np.matmul(np.transpose(c), x[:, 1])
In [54]: # Iterate through the cost vectors
         for k in range (1, 6):
             for i in range(23):
                 for j in range (30):
                     if k == 3:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + 0.85*data4[(k-1)*n + i*30 + j]
                     else:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + data4[(k-1)*30
In [55]: # Create a Gurobi model
         model = gp.Model()
In [56]:  # Define the decision variables
         x2 = model.addMVar(shape=m, lb=-1e30, ub=gp.GRB.INFINITY, name="x")
In [57]: # Set the objective function
         model.setObjective(c @ x2, sense=gp.GRB.MINIMIZE)
In [58]: # Add the constraints
         model.addConstr(Aeq @ x2 == beq, name="eq")
         model.addConstr(Aineq @ x2 <= bineq, name="ineq")</pre>
        <MConstr (3455,) *awaiting model update*>
Out[58]:
In [59]: # Solve the model
         model.optimize()
```

```
Gurobi Optimizer version 10.0.1 build v10.0.1rc0 (win64)
        CPU model: 12th Gen Intel(R) Core(TM) i5-1240P, instruction set [SSE2|AVX|AVX
         2]
         Thread count: 12 physical cores, 16 logical processors, using up to 16 threads
         Optimize a model with 4145 rows, 3450 columns and 10350 nonzeros
        Model fingerprint: 0xdde9ede1
        Coefficient statistics:
          Matrix range [1e+00, 1e+00]
          Objective range [1e+02, 2e+02]
          Bounds range [0e+00, 0e+00]
RHS range [1e+01, 3e+05]
          RHS range
                           [1e+01, 3e+05]
         Presolve removed 3451 rows and 5 columns
         Presolve time: 0.01s
         Presolved: 694 rows, 3445 columns, 6890 nonzeros
        Iteration Objective
                                     Primal Inf.
                                                    Dual Inf.
                                                                   Time
                    1.4056036e+08 1.671500e+04
                                                    0.000000e+00
                                                                      0s
              111
                   1.4091632e+08 0.000000e+00 0.000000e+00
                                                                       0s
         Solved in 111 iterations and 0.02 seconds (0.00 work units)
         Optimal objective 1.409163222e+08
In [60]: # Get the optimal solution
         x[:, 2] = model.getAttr('x')
         cost[:, 2] = np.matmul(np.transpose(c),x[:, 2])
In [61]: # Iterate through the cost vectors
         for k in range (1, 6):
             for i in range(23):
                 for j in range (30):
                     if k == 4:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + 0.85*data4[(k-1)*n + i*30 + j]
                     else:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + data4[(k-1)*30
In [62]: # Create a Gurobi model
         model = gp.Model()
In [63]: # Define the decision variables
         x3 = model.addMVar(shape=m, lb=-1e30, ub=gp.GRB.INFINITY, name="x")
In [64]: # Set the objective function
         model.setObjective(c @ x3, sense=gp.GRB.MINIMIZE)
In [65]: # Add the constraints
         model.addConstr(Aeq @ x3 == beq, name="eq")
         model.addConstr(Aineq @ x3 <= bineq, name="ineq")</pre>
        <MConstr (3455,) *awaiting model update*>
Out[65]:
In [66]: # Solve the model
         model.optimize()
```

```
Gurobi Optimizer version 10.0.1 build v10.0.1rc0 (win64)
        CPU model: 12th Gen Intel(R) Core(TM) i5-1240P, instruction set [SSE2|AVX|AVX
         2]
         Thread count: 12 physical cores, 16 logical processors, using up to 16 threads
         Optimize a model with 4145 rows, 3450 columns and 10350 nonzeros
        Model fingerprint: 0x15f5ddf2
        Coefficient statistics:
          Matrix range [1e+00, 1e+00]
          Objective range [2e+02, 3e+02]
          Bounds range [0e+00, 0e+00]
RHS range [1e+01, 3e+05]
          RHS range
                            [1e+01, 3e+05]
         Presolve removed 3451 rows and 5 columns
         Presolve time: 0.01s
         Presolved: 694 rows, 3445 columns, 6890 nonzeros
        Iteration Objective
                                     Primal Inf.
                                                    Dual Inf.
                                                                    Time
                    1.8927948e+08 1.192125e+04
                                                     0.000000e+00
                                                                       0s
               67
                    1.8946867e+08 0.000000e+00 0.000000e+00
                                                                       0s
         Solved in 67 iterations and 0.02 seconds (0.00 work units)
         Optimal objective 1.894686720e+08
In [67]: # Get the optimal solution
         x[:, 3] = model.getAttr('x')
         cost[:, 3] = np.matmul(np.transpose(c), x[:, 4])
In [68]: # Iterate through the cost vectors
         for k in range (1, 6):
             for i in range(23):
                 for j in range (30):
                     if k == 5:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + 0.85*data4[(k-1)*n + i*30 + j]
                     else:
                         c[(k-1)*n + i*30 + j] = c[(k-1)*n + i*30 + j] + data4[(k-1)*30
In [69]: # Create a Gurobi model
         model = gp.Model()
In [70]: # Define the decision variables
         x4 = model.addMVar(shape=m, lb=-1e30, ub=gp.GRB.INFINITY, name="x")
In [71]: | # Set the objective function
         model.setObjective(c @ x4, sense=gp.GRB.MINIMIZE)
In [72]: # Add the constraints
         model.addConstr(Aeq @ x4 == beq, name="eq")
         model.addConstr(Aineq @ x4 <= bineq, name="ineq")</pre>
        <MConstr (3455,) *awaiting model update*>
Out[72]:
In [73]: | # Solve the model
         model.optimize()
```

```
Gurobi Optimizer version 10.0.1 build v10.0.1rc0 (win64)
        CPU model: 12th Gen Intel(R) Core(TM) i5-1240P, instruction set [SSE2|AVX|AVX
        2]
        Thread count: 12 physical cores, 16 logical processors, using up to 16 threads
        Optimize a model with 4145 rows, 3450 columns and 10350 nonzeros
        Model fingerprint: 0xb9166a02
        Coefficient statistics:
          Matrix range [1e+00, 1e+00]
          Objective range [2e+02, 3e+02]
          Bounds range [0e+00, 0e+00]
RHS range [1e+01, 3e+05]
        Presolve removed 3451 rows and 5 columns
        Presolve time: 0.01s
        Presolved: 694 rows, 3445 columns, 6890 nonzeros
        Iteration Objective
                                    Primal Inf.
                                                   Dual Inf.
                                                                  Time
                    2.3820427e+08 7.553750e+03 0.000000e+00
                                                                     0s
              44
                    2.3832070e+08 0.000000e+00 0.000000e+00
                                                                     0s
        Solved in 44 iterations and 0.02 seconds (0.00 work units)
        Optimal objective 2.383206999e+08
In [74]: # Get the optimal solution
        x[:, 4] = model.getAttr('x')
        cost[:, 4] = np.matmul(np.transpose(c),x[:, 4])
In [75]: # Find the facility with minimal cost
        cost = list(cost)
         # added 1 to this line where calculate minimal to represent facilities from 1
        minimal = cost.index(min(cost))+1
        print("This policy should be implemented at facility: "+ str(minimal))
        This policy should be implemented at facility: 1
In [76]: # facility 1 is Alexandria city
```