



Models and Methods for Operation Research

Solving The Traveling Salesman Problem (TSP)

Guillermo Villanueva Benito

December 2021

Contents

1	TSP data	2
2	Obtaining an upper bound	4
3	Obtaining lower bounds	8
3.1	First Subtour Elimination Constraint (SEC-1)	10
3.2	Valid Inequality (different from SECs)	12
3.3	Gomory Cut	14
3.4	Second Subtour Elimination constraint (SEC-2)	17
4	Appendix	20
4.1	Section 2	20
4.2	Section 3	22

1 TSP data

We are considering the solution of the symmetric version of the TSP over a complete graph $G = (V, E)$ with $n = |V|$ nodes. More specifically, our graph have 12 nodes, $n = 12$. Moreover, since it is a complete graph the number of edges is

$$|E| = \frac{n(n-1)}{2} = 66 \quad (1)$$

The graph is non-directed and each edge (i, j) has its associated cost $c_{i,j}$ satisfying

$$c_{i,j} = c_{j,i} \quad (2)$$

in order to compute the solution of the symmetric TSP.

We consider the following cost matrix C

$$C = \begin{bmatrix} 0. & 0.723 & 1.046 & 0.811 & 0.588 & 0.547 & 0.97 & 0.452 & 0.361 & 0.444 & 0.605 & 0.359 \\ 0.723 & 0. & 0.844 & 0.618 & 0.455 & 0.186 & 0.276 & 0.534 & 0.467 & 0.306 & 0.707 & 0.39 \\ 1.046 & 0.844 & 0. & 0.255 & 0.498 & 0.791 & 0.773 & 0.597 & 0.716 & 0.954 & 0.463 & 0.975 \\ 0.811 & 0.618 & 0.255 & 0. & 0.244 & 0.543 & 0.609 & 0.359 & 0.468 & 0.701 & 0.288 & 0.72 \\ 0.588 & 0.455 & 0.498 & 0.244 & 0. & 0.33 & 0.551 & 0.156 & 0.231 & 0.467 & 0.255 & 0.479 \\ 0.547 & 0.186 & 0.791 & 0.543 & 0.33 & 0. & 0.425 & 0.369 & 0.285 & 0.185 & 0.562 & 0.248 \\ 0.97 & 0.276 & 0.773 & 0.609 & 0.551 & 0.425 & 0. & 0.681 & 0.661 & 0.578 & 0.798 & 0.658 \\ 0.452 & 0.534 & 0.597 & 0.359 & 0.156 & 0.369 & 0.681 & 0. & 0.134 & 0.448 & 0.212 & 0.431 \\ 0.361 & 0.467 & 0.716 & 0.468 & 0.231 & 0.285 & 0.661 & 0.134 & 0. & 0.324 & 0.344 & 0.299 \\ 0.444 & 0.306 & 0.954 & 0.701 & 0.467 & 0.185 & 0.578 & 0.448 & 0.324 & 0. & 0.659 & 0.088 \\ 0.605 & 0.707 & 0.463 & 0.288 & 0.255 & 0.562 & 0.798 & 0.212 & 0.344 & 0.659 & 0. & 0.642 \\ 0.359 & 0.39 & 0.975 & 0.72 & 0.479 & 0.248 & 0.658 & 0.431 & 0.299 & 0.088 & 0.642 & 0. \end{bmatrix}$$

(3)

In order to compute cost matrix C, we have used a simple python code, Listing (1). We have randomly generated 12 points in the region $[0, 1] \times [0, 1] \subset \mathbb{R}^2$ associated with the position of the 12 nodes of the graph. For each node $v_i \in V$ it position p_i is

$$p_i = (x_i, y_i) \quad (4)$$

Then, the cost matrix C is the distance matrix. More specifically, for each pair of nodes (v_i, v_j) its associated cost $c_{i,j}$ is given by

$$c_{i,j} = \|p_i - p_j\| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (5)$$

A graphical representation of this graph is shown in Figure (1).

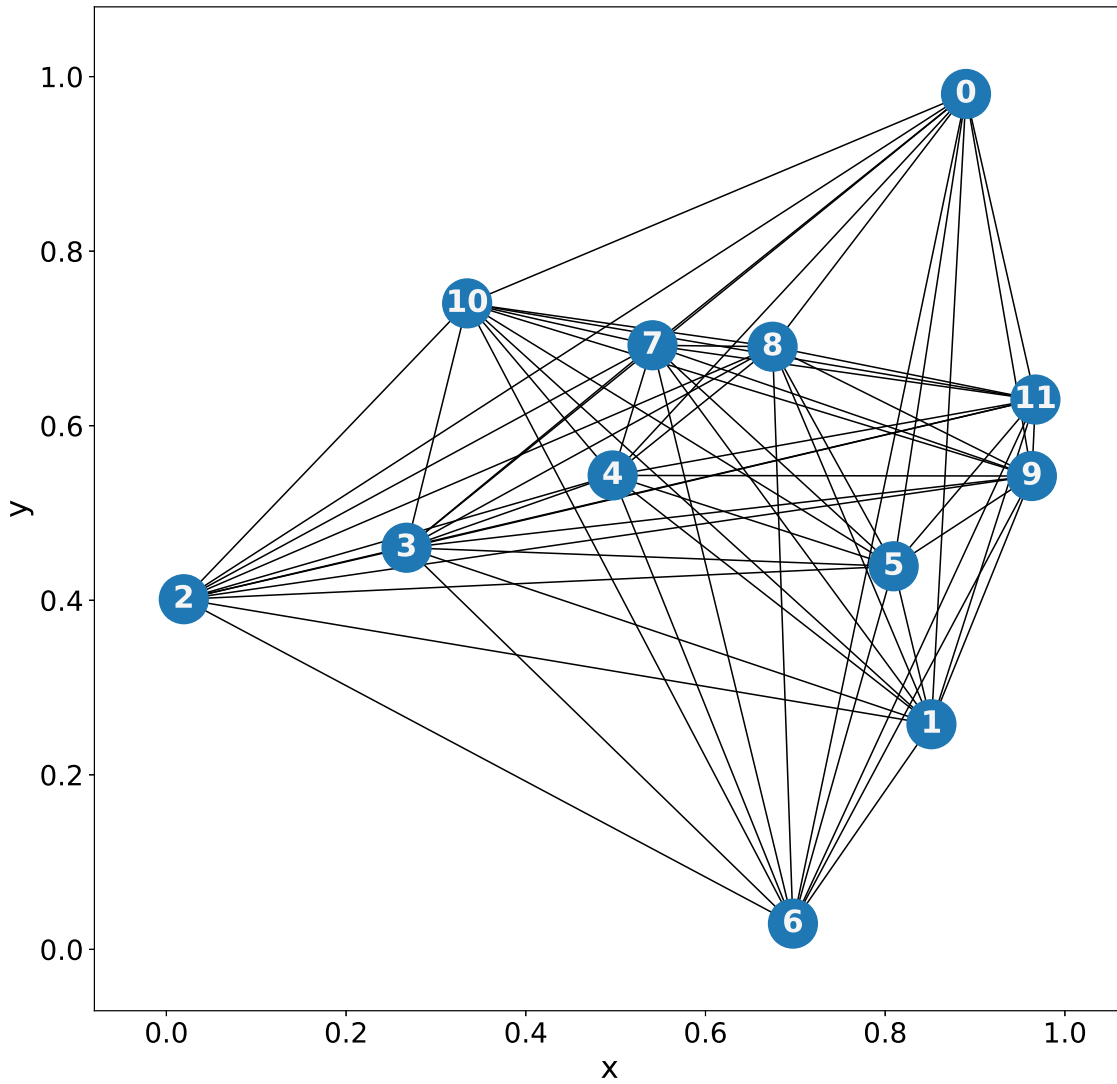


Figure 1: Graph representation

Listing 1: Code section 1

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 import networkx
```

```

4 import random as rn
5
6 # Create random coordinates
7 A = np.random.random((12,2))
8 x = A[:,0];
9 y = A[:,1];
10
11 # Compute cost matrix C (distance matrix)
12 C = np.zeros((12,12));
13 for i in range(len(x)):
14     for j in range(len(y)):
15         C[i,j] = np.round(np.sqrt((x[i]-x[j])**2+(y[i]-y[j])**2),3)
16
17 # Create complete graph with n = 12
18 G = networkx.complete_graph(12)
19
20 # Set the position of nodes
21 pos = networkx.spring_layout(G)
22 for i in range(12):
23     pos[i] = A[i,:]
24
25 # Plot the graph
26 fig, ax = plt.subplots(figsize=(10, 10))
27 networkx.draw(G, pos, with_labels=True,font_color="whitesmoke",ax=ax,node_size
↪ = 1000,font_weight='bold',font_size = 20)
28 limits=plt.axis('on') # turns on axis
29 plt.ylabel('y',fontsize=20)
30 plt.xlabel('x',fontsize=20)
31 ax.tick_params(left=True, bottom=True, labelleft=True,
↪ labelbottom=True,labelsize=18)

```

2 Obtaining an upper bound

In this section we program an heuristic for getting a feasible solution for the symmetric TSP (STSP). The heuristic will consist of two different parts: one constructive part, in which a greedy procedure is applied, and a second part, which consists of an improvement phase.

For the constructive part we will use the Nearest Neighbor primal heuristic.

Nearest Neighbor (NN) heuristic: Start at an arbitrary node i_1 and construct a path $i_1, i_2, \dots, i_j, i_{j+1}, \dots, i_n$ where $i_{j+1} = \arg(\min(c_{i,k} : k \in V \setminus \{i_1, i_2, \dots, i_j\}))$.

For the improvement phase, we will apply the 2-Interchange local search heuristic to obtain better upper bounds for the original TSP.

2-Interchange local search heuristic: Start with a given tour (feasible solution) and replace each pair of non-adjacent edges in the tour with the unique pair of replacement edges if the resulting tour has a lower weight.

The main results of this section are shown in Figure (2). Here, we have applied the 2-Interchange local search heuristic to 12 initial tours. Each tour is the output solution for the NN heuristic taking a different initial arbitrary node. For instance, the red curve (NN(3)) shows the different improving tours obtained by the 2-Interchange local search heuristic taking as initial tour, the tour solution for the NN heuristic with initial node, node number 3. The initial upper bound is the upper bound obtained using only the NN heuristic.

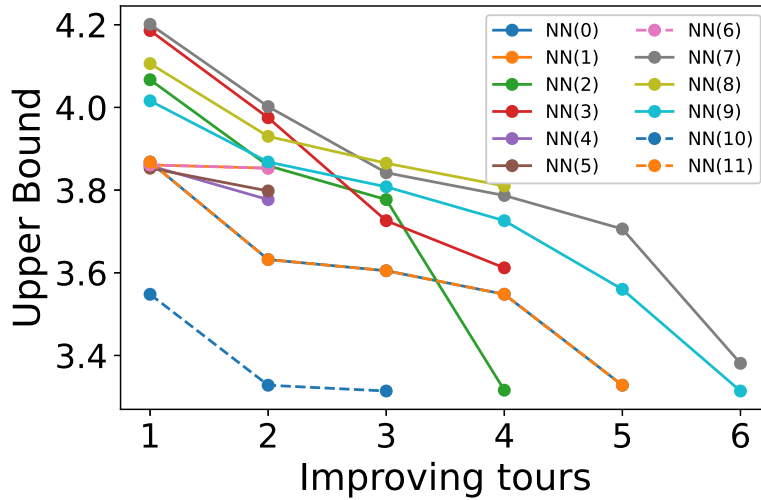


Figure 2: Upper bounds as a function of the different improving tours obtained by the 2-Interchange heuristic. The first upper bound is the upper bound obtained using the NN heuristic with initial node given by the color legend.

As expected, the local search heuristic improves the upper bound obtained by the greedy heuristic. We notice that the best upper bound has been obtained with NN(9) and NN(10). In both cases, the obtained upper bound is

$$\overline{z^*} = 3.314 \quad (6)$$

and the resulting tour is shown in Figure (3).

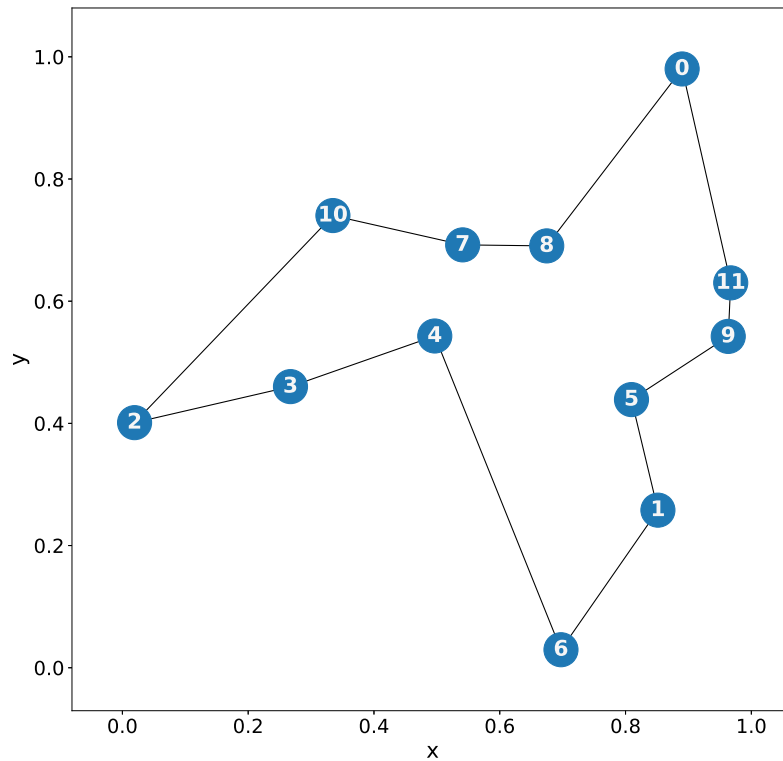


Figure 3: Tour associated with the best upper bound.

The complete list of successive tours with its associated cost is given in the Appendix. The python code used to implement the heuristic is shown below, Listing (2).

Listing 2: Code section 2

```

1 import numpy as np
2
3 # Save results in file test.txt
4 a = open('test.txt', 'w')
5 # NN heuristic for each initial node
6 for k in np.arange(0,12,1):
7
8     # mark used node
9     nodes = np.zeros(12);
10    nodes[k] = 1;
11    # tour

```

```

12  tour = [k];
13  # Initialize
14  ok = len(np.where(nodes==0)[0]);
15  i0 = k;
16  while ok > 0:
17      pos = np.where(nodes==0)[0];
18      # Find nearest neighbor
19      i1 = pos[np.where(D[pos,i0]== min(D[pos,i0]))[0]];
20      # Add nearest neighbor
21      tour.append(i1[0])
22      # Update cost
23      cost[k] = cost[k] + D[i0,i1];
24      # mark used node
25      nodes[i1] = 1;
26      # Updates
27      i0 = i1;
28      ok = len(np.where(nodes==0)[0]);
29
30  # Add final edge to close tour
31  cost[k] = cost[k]+ D[i1,k];
32  tour.append(k)
33  # Save results
34  a.write('NN(%s'%k+'): \n'+ '%s' % tour + ' -- z* = %s\n' % cost[k])
35  # 2-Interchange heuristic for each NN tour solution
36  for i in np.arange(0,10,1):
37
38      for j in np.arange(i+2,12,1):
39          d1 = D[tour[i],tour[i+1]] + D[tour[j],tour[j+1]];
40          d2 = D[tour[i],tour[j]] + D[tour[i+1],tour[j+1]];
41
42          # Do swap if interchange improves upper bound
43          if d2 < d1:
44              tour[i+1:j+1] = np.flip(tour[i+1:j+1])
45              cost[k] = cost[k]-d1+d2;
46              a.write('%s' % tour+ ' -- z* = %s\n' % cost[k])
47  a.close()

```


3 Obtaining lower bounds

Our goal is to solve the Symmetric Travelling Salesman Problem (P) over the complete graph built in the previous section

$$\begin{aligned} \min \quad & \sum_{(i,j) \in E} c_{i,j} x_{i,j} \\ \text{s.t.} \quad & \sum_{i < j} x_{i,j} + \sum_{j < i} x_{j,i} = 2 \quad \forall i \in V \\ & x_{i,j} \in \{0, 1\} \quad \forall (i, j) \in E \end{aligned} \tag{P}$$

In previous section, we obtained several upper bounds for the problem by applying an heuristic procedure. In this section, we will solve some relaxations of problem (P) in order to obtain lower bounds.

In order to find lower bounds we will first solve the following linear relaxation (RP1) of the problem in which Subtour Elimination Constraints (SECs) are not taken into account.

$$\begin{aligned} \min \quad & \sum_{(i,j) \in E} c_{i,j} x_{i,j} \\ \text{s.t.} \quad & \sum_{i < j} x_{i,j} + \sum_{j < i} x_{j,i} = 2 \quad \forall i \in V \\ & 0 \leq x_{i,j} \leq 1 \end{aligned} \tag{RP1}$$

Afterwards, we will firstly add to problem (RP1) a violated SEC and solve the new relaxed problem (RP2). Secondly, we will add to problem (RP2) a violated valid inequality (different from SECs) and solve the new relaxed problem (RP3). Thirdly, we will add to problem (RP3) a gomory cut and solve the new relaxed problem (RP4). Finally, we will add to problem (RP4) a new violated SEC and solve the new relaxed problem (RP5).

We notice that the problem could be solved by only adding SECs to the initial problem formulation (RP1). However, we have decided to apply three different procedures (SEC, valid inequality and gomory cut) to improve the lower bound so as to have a better understanding of those procedures.

In order to solve the different relaxed problems we have used AMPL-CPLEX. However, in order to compute the gomory cut for problem (RP4) we have used the Python API for CPLEX.

The following solution has been obtained for (RP1),

$$x^{1*} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1/2 & 1 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad z^{1*} = 3.249 \quad (7)$$

Figure (4) shows the graphical solution of (RP1). As it can be seen, the solution of problem (RP1) is not a solution for the original TSP problem.

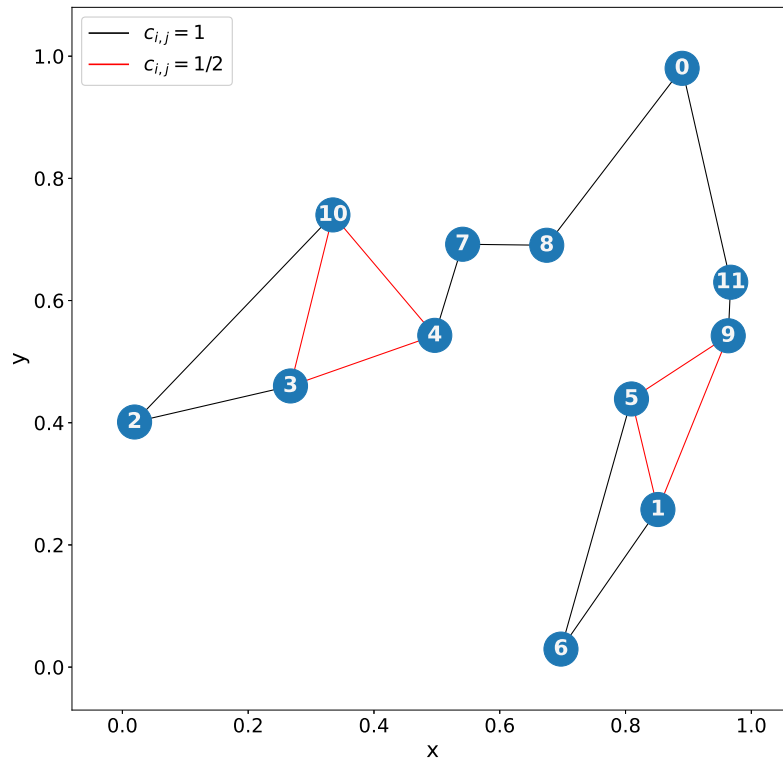


Figure 4: (RP1) solution

3.1 First Subtour Elimination Constraint (SEC-1)

We look for a Subtour Elimination Constraint (SEC) violated by x^{1*} and add it to the formulation of (RP1). In order to find it we will use the SEC identification heuristic method.

SEC identification heuristic method: Let x^* be the current solution and $G(x^*)$ the graph induced by x^* .

1. If there exist (i, j) such that $x_{i,j}^* > 1$, then the nodes involved in (i, j) define the SEC violated by x^* .
2. Else if $x_{i,j}^* < 1, \forall (i, j) \in G(x^*)$, then there are not violated SEC in the graph detected by the heuristic method.
3. Else if there exists (i, j) such that $x_{i,j}^* = 1$ then we generate a pseudo-node $\hat{i}_{i,j}$ that results from aggregating i and j and
 - If for some node k , $x_{i,k}^* > 0$ and $x_{j,k}^* > 0$ then we create an edge $(\hat{i}_{i,j}, k)$ with value $x_{\hat{i}_{i,j},k}^* = x_{i,k}^* + x_{j,k}^*$.
 - If for some node k , $x_{i,k}^* > 0$ or $x_{j,k}^* > 0$ then we create an edge $(\hat{i}_{i,j}, k)$ with value $x_{\hat{i}_{i,j},k}^* = x_{i,k}^*$ or $x_{\hat{i}_{i,j},k}^* = x_{j,k}^*$.

Applying the SEC identification heuristic method to $G(x^{1*})$ we observe that the subset $S_1 = \{2, 3, 10\} \subset V$ define a SEC violated by x^{1*} : if we consider the pseudo-node resulting from aggregating nodes 2 and 3, $\hat{i}_{2,3}$, we observe that the edge $(\hat{i}_{2,3}, 10)$ has $x_{\hat{i}_{2,3},10}^* = 1.5 > 1$.

Therefore, the SEC violated by x^{1*} and given by S_1 (SEC-1) is

$$\sum_{\substack{(i,j) \in S_1 \\ i < j}} x_{i,j} \leq |S_1| - 1 \quad (\text{SEC-1})$$

We add (SEC-1) to the formulation of (RP1) obtaining (RP2)

$$\begin{aligned} \min \quad & \sum_{(i,j) \in E} c_{i,j} x_{i,j} \\ \text{s.t.} \quad & \sum_{i < j} x_{i,j} + \sum_{j < i} x_{j,i} = 2 \quad \forall i \in V \\ & (\text{SEC-1}) \\ & 0 \leq x_{i,j} \leq 1 \end{aligned} \quad (\text{RP2})$$

The following solution has been obtained for (RP2),

$$x^{2*} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1/2 & 1 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad z^{2*} = 3.255 \quad (8)$$

Figure (5) shows the graphical solution of (RP2).

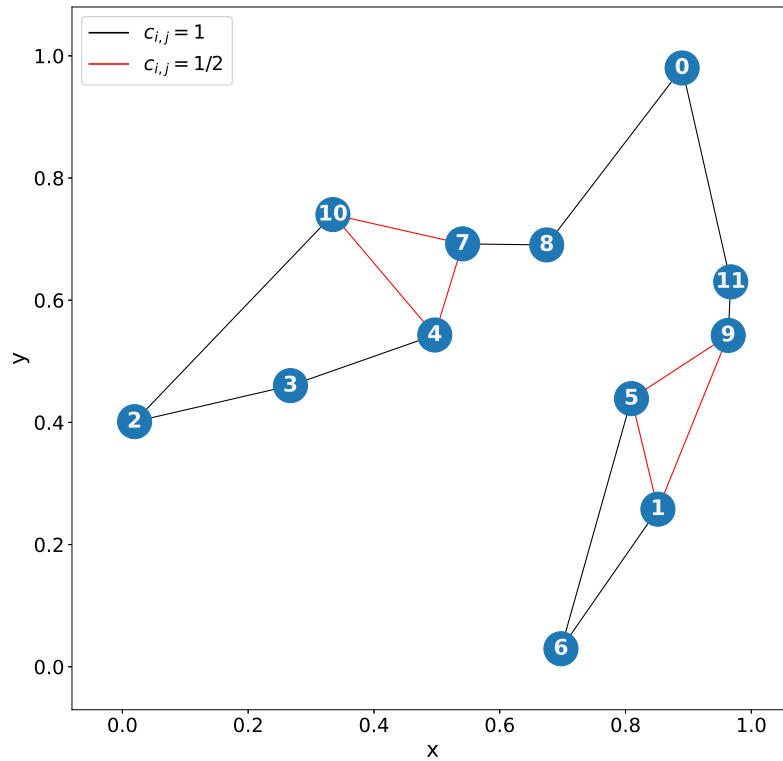


Figure 5: (RP2) solution

Again, solution to (RP2) is still not being a solution to the original TSP problem.

3.2 Valid Inequality (different from SECs)

Now we look for some valid inequality for the TSP (different from the SEC's) which be violated by x^{2*} . In order to find it, we will compute a Chvátal-Gomory inequality violated by x^{2*} .

Step 1: We sum up the degree equations for the set of nodes in $H = \{1, 5, 9\}$. Let $c(i)$ be the degree equation associated with node i , that is

$$c(i) : \sum_{i < j} x_{ij} + \sum_{j < i} x_{ji} = 2 \quad (9)$$

Then, we have

$$c(1) + c(5) + c(9) = 2 \times 3 \quad (10)$$

Step 2: Since, all variables x_{ij} satisfy $0 \leq x_{ij} \leq 1$, then from Eq. (10) we have the inequality

$$2 \sum_{\substack{(i,j) \in H \\ i < j}} x_{i,j} + x_{1,6} + x_{5,6} + x_{9,11} \leq 2 \times 3 \quad (11)$$

Step 3: We sum to Eq. (11) the inequalities (upper bounds)

$$x_{1,6} \leq 1, \quad x_{5,6} \leq 1, \quad x_{9,11} \leq 1 \quad (12)$$

and we obtain the following inequality

$$2 \sum_{\substack{(i,j) \in H \\ i < j}} x_{i,j} + 2(x_{1,6} + x_{5,6} + x_{9,11}) \leq 2 \times 3 + 3 \quad (13)$$

Multiplying Eq. (13) by 1/2 and since

$$\sum_{\substack{(i,j) \in H \\ i < j}} x_{i,j} = x_{1,5} + x_{1,9} + x_{5,9} \quad (14)$$

we obtain

$$x_{1,5} + x_{1,9} + x_{5,9} + x_{1,6} + x_{5,6} + x_{9,11} \leq 3 + 3/2 \quad (15)$$

Now, since the the left hand side for the TSP should be integer-valued we can round down the right hand side to obtain a valid inequality for the STP, which in fact is violated by x_{2*}

$$x_{1,5} + x_{1,9} + x_{5,9} + x_{1,6} + x_{5,6} + x_{9,11} \leq 4 \quad (\text{INEQ-1})$$

Therefore, we add (INEQ-1) to the formulation of (RP2) in order to obtain (RP3). We notice that (INEQ-1) belongs to a type of inequalities known as *Comb inequalities*.

$$\begin{aligned}
\min \quad & \sum_{(i,j) \in E} c_{i,j} x_{i,j} \\
\text{s.t.} \quad & \sum_{i < j} x_{i,j} + \sum_{j < i} x_{j,i} = 2 \quad \forall i \in V \\
& \text{(SEC-1)} \\
& \text{(INEQ-1)} \\
& 0 \leq x_{i,j} \leq 1
\end{aligned} \tag{RP3}$$

The following solution has been obtained for (RP3),

$$x^{3*} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 1/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad z^{3*} = 3.2715 \tag{16}$$

Figure (6) shows the graphical solution of (RP3).

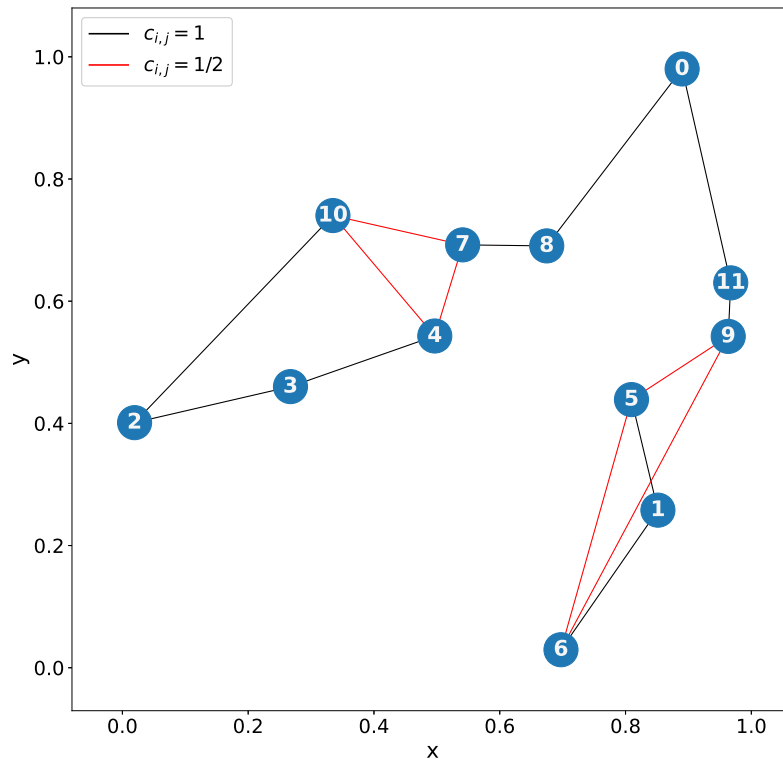


Figure 6: (RP3) solution

Again, solution to (RP3) is still not being a solution to the original TSP problem.

3.3 Gomory Cut

Now, we try to identify some Gomory cut violated by x^{3*} . In order to compute it, we have used the Python API for CPLEX and instance methods `binvarow()` and `basis.write()` which provide the i -th row of the optimal LP tableau and basic variables information, respectively.

In order to use the Python API for CPLEX we have firstly export the AMPL model into a `.mps` format file (Appendix: `tsp.mps`). The code below, Listing (3) shows the python code used.

Listing 3: Code section 3 (Gomory cut)

```

1 import cplex
2 import numpy as np
3

```

```

4 # Load model( file .mps)
5 c = cplex.Cplex()
6 out = c.set_results_stream(None)
7 out = c.set_log_stream(None)
8 c.read("tsp.mps")
9
10 #Solve problem
11 c.solve()
12
13 # Compute Simplex Tableau
14 Tableau = np.zeros((14,132));
15 cont = 0;
16 for tableau_row in c.solution.advanced.binvarow():
17     Tableau[cont,:] = tableau_row;
18     cont = cont+1;
19
20 # Basis info
21 c.solution.basis.write("basis.mps")
22
23 #Solution
24 SOL = c.solution.get_values();

```

We will compute the gomory cut associated with the basic variable $x_{5,8}$ which has a non-integer value ($x_{5,8}^{3*} = 1/2$). The 8-row is the one associated with basic variable $x_{5,8}$ (Appendix: .col + basis.mps). Then, according to the Tableau, the following equality must be satisfied by any feasible solution (in particular by x^{3*})

$$\begin{aligned}
& x_{5,8} - \frac{1}{2}(x_{1,3} + x_{1,4} + x_{1,11} + x_{2,3} + x_{2,4} + x_{2,11} + x_{3,6} + x_{3,7} + x_{3,9} + x_{3,10} + x_{3,12} + x_{4,6} + x_{4,7} + \\
& \quad + x_{4,9} + x_{4,10} + x_{4,12} + x_{6,11} + x_{7,11} + x_{9,11} + x_{10,11} + x_{11,12}) + \\
& + \frac{1}{2}(x_{1,5} + x_{1,8} + x_{2,5} + x_{2,8} + x_{5,6} + x_{5,7} + x_{5,9} + x_{5,10} + x_{5,12} + x_{6,8} + x_{7,8} + x_{8,9} + x_{8,10} + x_{8,12}) = 1/2
\end{aligned} \tag{17}$$

In order to compute the Gomory cut (GC-1), we notice that variables $x_{i,j}$ are integer and non-negative and we round down the right hand side and coefficients on the left hand side and we obtain,

$$\begin{aligned}
& x_{5,8} - \frac{1}{2}(x_{1,3} + x_{1,4} + x_{1,11} + x_{2,3} + x_{2,4} + x_{2,11} + x_{3,6} + x_{3,7} + x_{3,9} + x_{3,10} + x_{3,12} + x_{4,6} + x_{4,7} + \\
& \quad + x_{4,9} + x_{4,10} + x_{4,12} + x_{6,11} + x_{7,11} + x_{9,11} + x_{10,11} + x_{11,12}) \leq 0
\end{aligned} \tag{18}$$

Therefore, we add (GC-1) to the formulation of (RP3) in order to obtain (RP4).

$$\begin{aligned}
\min \quad & \sum_{(i,j) \in E} c_{i,j} x_{i,j} \\
\text{s.t.} \quad & \sum_{i < j} x_{i,j} + \sum_{j < i} x_{j,i} = 2 \quad \forall i \in V \\
& \text{(SEC-1)} \\
& \text{(INEQ-1)} \\
& \text{(GC-1)} \\
& 0 \leq x_{i,j} \leq 1
\end{aligned} \tag{P3}$$

The following solution has been obtained to (RP4), (Appendix: .sol)

$$x^{4*} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1/3 & 0 & 0 & 0 & 2/3 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/3 & 0 & 0 & 2/3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1/3 & 0 & 0 & 2/3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 2/3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad z^{4*} = 3.29 \tag{19}$$

Figure (7) shows the graphical solution of (RP4).

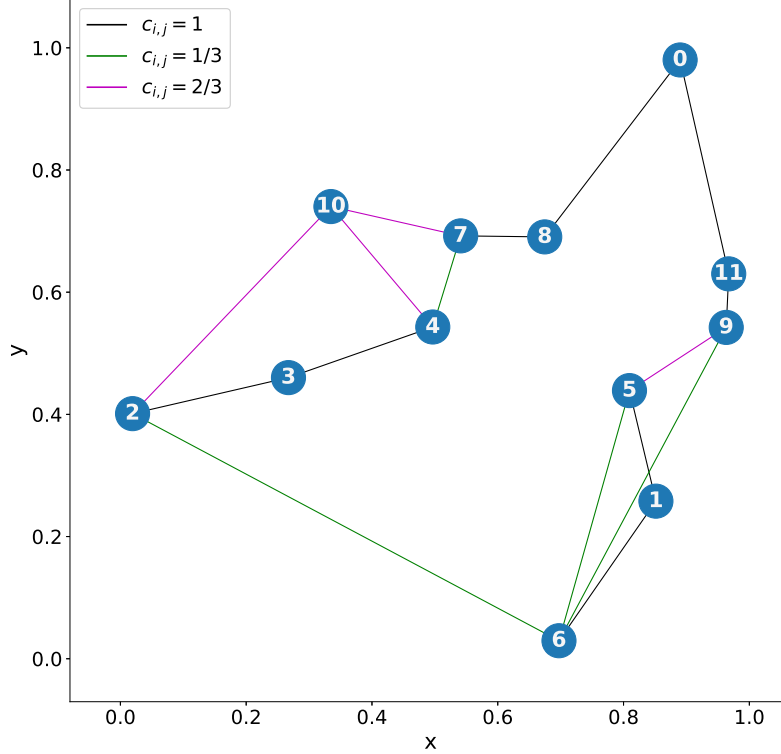


Figure 7: (RP4) solution

Again, solution to (RP4) is still not being a solution to the original TSP problem.

3.4 Second Subtour Elimination constraint (SEC-2)

We look for a Subtour Elimination Constraint (SEC) violated by x^{4*} and add it to the formulation of (RP4). In order to find it we will use the SEC identification heuristic method previously explained.

Applying the SEC identification heuristic method to $G(x^{4*})$ we observe that the subset $S_2 = \{1, 5, 6\} \subset V$ defines a SEC violated by x^{4*} : if we consider the pseudo-node resulting from aggregating nodes 1 and 6, $\hat{i}_{1,6}$, we observe that the edge $(\hat{i}_{1,6}, 5)$ has $x_{\hat{i}_{1,6},5}^* = 1 + 1/3 > 1$.

Therefore, the SEC violated by x^{4*} and given by S_2 (SEC-2) is

$$\sum_{\substack{(i,j) \in S_2 \\ i < j}} x_{i,j} \leq |S_2| - 1 \quad (\text{SEC-2})$$

We add (SEC-2) to the formulation of (RP4) obtaining (RP5)

$$\begin{aligned}
\min \quad & \sum_{(i,j) \in E} c_{i,j} x_{i,j} \\
\text{s.t.} \quad & \sum_{i < j} x_{i,j} + \sum_{j < i} x_{j,i} = 2 \quad \forall i \in V \\
& \text{(SEC-1)} \\
& \text{(INEQ-1)} \\
& \text{(GC-1)} \\
& \text{(SEC-2)} \\
& 0 \leq x_{i,j} \leq 1
\end{aligned} \tag{RP5}$$

The following solution has been obtained for (RP5),

$$x^{5*} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad z^{5*} = 3.314 \tag{20}$$

Clearly, solution to (RP5) is the solution to the TSP as it is an integer solution and no SEC is violated. Moreover, for this solution the lower bound obtained equals the best upper bound obtained in the previous section

$$z^* = \overline{z^*} = \underline{z^*} \tag{21}$$

which shows optimality.

Figure (8) shows the corresponding lower bounds for the TSP obtained in the relaxed problems (RP1), (RP2), (RP3), (RP4) and (RP5) just solved.

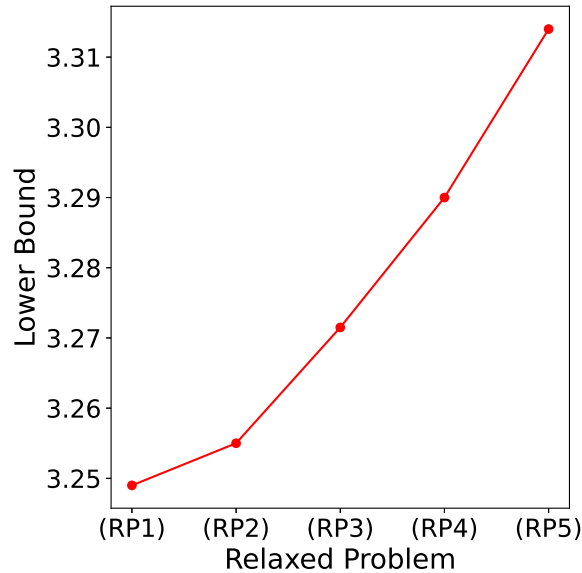


Figure 8: TSP Lower bounds for the different relaxed problems solved.

As expected, as the problem becomes more restrictive, lower bounds increase.

Below, we show the main AMPL-CPLEX files (.mod, .dat) used in this section.

Listing 4: Section 3 (.mod)

```

# parameters
param n;
set nodes ordered := {1..n};
set edges := {i in nodes, j in nodes};

set nodes1 ordered := {3,4,11};
set edges1 := {i in nodes1, j in nodes1};

set nodes2 ordered := {2,6,7};
set edges2 := {i in nodes2, j in nodes2};

param c {(i,j) in edges};
var X {(i,j) in edges} >=0, <=1;

#Objective function
minimize fobj : sum {(i,j) in edges} (c[i,j]*X[i,j]);

#Constraints
subject to cc1 {i in nodes}: sum{(i,j) in edges: i < j} (X[i,j]) + sum{(i,j) in edges: j < i}
(X[j,i]) = 2;

```

```

subject to cc2: sum{(i,j) in edges1:i < j} (X[i,j]) <= 2;
subject to cc3: X[2,6]+X[2,10]+X[6,10]+X[2,7]+X[6,7]+X[10,12] <= 4;
subject to cc4: X[5,8] -
    X[1,3]-X[1,4]-X[1,11]-X[2,3]-X[2,4]-X[2,11]-X[3,6]-X[3,7]-X[3,9]-X[3,10]-X[3,12]-X[4,6]-
    -X[4,7]-X[4,9]-X[4,10]-X[4,12]-X[6,11]-X[7,11]-X[9,11]-X[10,11]-X[11,12] <= 0;
subject to cc5: sum{(i,j) in edges2:i < j} (X[i,j]) <= 2;

```

Listing 5: Section 3 (.dat)

```

param n := 12;

param c: 1 2 3 4 5 6 7 8 9 10 11 12 :=

1 0.    0.723 1.046 0.811 0.588 0.547 0.97  0.452 0.361 0.444 0.605 0.359
2 0.723 0.    0.844 0.618 0.455 0.186 0.276 0.534 0.467 0.306 0.707 0.39
3 1.046 0.844 0.    0.255 0.498 0.791 0.773 0.597 0.716 0.954 0.463 0.975
4 0.811 0.618 0.255 0.    0.244 0.543 0.609 0.359 0.468 0.701 0.288 0.72
5 0.588 0.455 0.498 0.244 0.    0.33  0.551 0.156 0.231 0.467 0.255 0.479
6 0.547 0.186 0.791 0.543 0.33  0.    0.425 0.369 0.285 0.185 0.562 0.248
7 0.97  0.276 0.773 0.609 0.551 0.425 0.    0.681 0.661 0.578 0.798 0.658
8 0.452 0.534 0.597 0.359 0.156 0.369 0.681 0.    0.134 0.448 0.212 0.431
9 0.361 0.467 0.716 0.468 0.231 0.285 0.661 0.134 0.    0.324 0.344 0.299
10 0.444 0.306 0.954 0.701 0.467 0.185 0.578 0.448 0.324 0.    0.659 0.088
11 0.605 0.707 0.463 0.288 0.255 0.562 0.798 0.212 0.344 0.659 0.    0.642
12 0.359 0.39  0.975 0.72  0.479 0.248 0.658 0.431 0.299 0.088 0.642 0.
;

```

4 Appendix

4.1 Section 2

Complete list of successive tours with its associated cost obtained by the heuristic explained in section 2.

Listing 6: Heuristic method

```

NN(0):
[0, 11, 9, 5, 1, 6, 4, 7, 8, 10, 3, 2, 0] -- z* = 3.8679999999999994
[0, 11, 9, 5, 1, 6, 2, 3, 10, 8, 7, 4, 0] -- z* = 3.6319999999999997
[0, 11, 9, 5, 1, 6, 2, 3, 4, 7, 8, 10, 0] -- z* = 3.6049999999999995
[0, 11, 9, 5, 1, 6, 2, 3, 4, 8, 7, 10, 0] -- z* = 3.5479999999999996
[0, 11, 9, 5, 1, 6, 2, 3, 4, 10, 7, 8, 0] -- z* = 3.328
NN(1):

```

[1, 5, 9, 11, 8, 7, 4, 3, 2, 10, 0, 6, 1] -- z* = 3.8609999999999998
[1, 0, 10, 2, 3, 4, 7, 8, 11, 9, 5, 6, 1] -- z* = 3.8529999999999998

NN(2):

[2, 3, 4, 7, 8, 5, 9, 11, 0, 10, 1, 6, 2] -- z* = 4.0669999999999999
[2, 3, 10, 0, 11, 9, 5, 8, 7, 4, 1, 6, 2] -- z* = 3.8589999999999999
[2, 3, 10, 4, 7, 8, 5, 9, 11, 0, 1, 6, 2] -- z* = 3.7769999999999992
[2, 3, 10, 4, 7, 8, 0, 11, 9, 5, 1, 6, 2] -- z* = 3.3159999999999999

NN(3):

[3, 4, 7, 8, 5, 9, 11, 0, 10, 2, 6, 1, 3] -- z* = 4.1860000000000001
[3, 2, 10, 0, 11, 9, 5, 8, 7, 4, 6, 1, 3] -- z* = 3.9750000000000001
[3, 2, 10, 0, 11, 9, 5, 1, 6, 4, 7, 8, 3] -- z* = 3.7260000000000001
[3, 2, 10, 0, 11, 9, 5, 1, 6, 8, 7, 4, 3] -- z* = 3.6120000000000001

NN(4):

[4, 7, 8, 5, 9, 11, 0, 10, 3, 2, 6, 1, 4] -- z* = 3.859
[4, 7, 8, 5, 9, 11, 0, 1, 6, 2, 3, 10, 4] -- z* = 3.777

NN(5):

[5, 9, 11, 8, 7, 4, 3, 2, 10, 0, 1, 6, 5] -- z* = 3.8529999999999998
[5, 0, 10, 2, 3, 4, 7, 8, 11, 9, 1, 6, 5] -- z* = 3.798

NN(6):

[6, 1, 5, 9, 11, 8, 7, 4, 3, 2, 10, 0, 6] -- z* = 3.8609999999999998
[6, 1, 0, 10, 2, 3, 4, 7, 8, 11, 9, 5, 6] -- z* = 3.8529999999999998

NN(7):

[7, 8, 4, 3, 2, 10, 5, 9, 11, 0, 1, 6, 7] -- z* = 4.201
[7, 10, 2, 3, 4, 8, 5, 9, 11, 0, 1, 6, 7] -- z* = 4.002
[7, 10, 2, 3, 6, 1, 0, 11, 9, 5, 8, 4, 7] -- z* = 3.842
[7, 10, 2, 3, 6, 1, 9, 11, 0, 5, 8, 4, 7] -- z* = 3.787
[7, 10, 2, 3, 6, 1, 5, 0, 11, 9, 8, 4, 7] -- z* = 3.7059999999999995
[7, 10, 2, 3, 6, 1, 5, 9, 11, 0, 8, 4, 7] -- z* = 3.3809999999999993

NN(8):

[8, 7, 4, 3, 2, 10, 5, 9, 11, 0, 1, 6, 8] -- z* = 4.106
[8, 7, 10, 2, 3, 4, 5, 9, 11, 0, 1, 6, 8] -- z* = 3.9299999999999997
[8, 7, 10, 2, 3, 6, 1, 0, 11, 9, 5, 4, 8] -- z* = 3.8649999999999993
[8, 7, 10, 2, 3, 6, 1, 9, 11, 0, 5, 4, 8] -- z* = 3.8099999999999996

NN(9):

[9, 11, 5, 1, 6, 4, 7, 8, 10, 3, 2, 0, 9] -- z* = 4.016
[9, 11, 0, 2, 3, 10, 8, 7, 4, 6, 1, 5, 9] -- z* = 3.868
[9, 11, 0, 3, 2, 10, 8, 7, 4, 6, 1, 5, 9] -- z* = 3.808
[9, 11, 0, 10, 2, 3, 8, 7, 4, 6, 1, 5, 9] -- z* = 3.7259999999999995
[9, 11, 0, 8, 3, 2, 10, 7, 4, 6, 1, 5, 9] -- z* = 3.5599999999999996
[9, 11, 0, 8, 7, 10, 2, 3, 4, 6, 1, 5, 9] -- z* = 3.3139999999999996

NN(10):

[10, 7, 8, 4, 3, 2, 6, 1, 5, 9, 11, 0, 10] -- z* = 3.548
[10, 7, 8, 0, 11, 9, 5, 1, 6, 2, 3, 4, 10] -- z* = 3.3280000000000003
[10, 7, 8, 0, 11, 9, 5, 1, 6, 4, 3, 2, 10] -- z* = 3.314

NN(11):

```

[11, 9, 5, 1, 6, 4, 7, 8, 10, 3, 2, 0, 11] -- z* = 3.8679999999999994
[11, 9, 5, 1, 6, 2, 3, 10, 8, 7, 4, 0, 11] -- z* = 3.6319999999999997
[11, 9, 5, 1, 6, 2, 3, 4, 7, 8, 10, 0, 11] -- z* = 3.6049999999999995
[11, 9, 5, 1, 6, 2, 3, 4, 8, 7, 10, 0, 11] -- z* = 3.5479999999999996
[11, 9, 5, 1, 6, 2, 3, 4, 10, 7, 8, 0, 11] -- z* = 3.328

```

4.2 Section 3

Listing 7: tsp.mps

```

NAME          tsp
ROWS
E R0001
E R0002
E R0003
E R0004
E R0005
E R0006
E R0007
E R0008
E R0009
E R0010
E R0011
E R0012
L R0013
L R0014
N R0015
COLUMNS
C0001  R0001  1
C0001  R0002  1
C0001  R0015  0.723
C0002  R0001  1
C0002  R0003  1
C0002  R0015  1.046
C0003  R0001  1
C0003  R0004  1
C0003  R0015  0.811
C0004  R0001  1
C0004  R0005  1
C0004  R0015  0.588
C0005  R0001  1
C0005  R0006  1
C0005  R0015  0.547
C0006  R0001  1
C0006  R0007  1

```

C0006	R0015	0.97
C0007	R0001	1
C0007	R0008	1
C0007	R0015	0.452
C0008	R0001	1
C0008	R0009	1
C0008	R0015	0.361
C0009	R0001	1
C0009	R0010	1
C0009	R0015	0.444
C0010	R0001	1
C0010	R0011	1
C0010	R0015	0.605
C0011	R0001	1
C0011	R0012	1
C0011	R0015	0.359
C0012	R0015	0.723
C0013	R0002	1
C0013	R0003	1
C0013	R0015	0.844
C0014	R0002	1
C0014	R0004	1
C0014	R0015	0.618
C0015	R0002	1
C0015	R0005	1
C0015	R0015	0.455
C0016	R0002	1
C0016	R0006	1
C0016	R0014	1
C0016	R0015	0.186
C0017	R0002	1
C0017	R0007	1
C0017	R0014	1
C0017	R0015	0.276
C0018	R0002	1
C0018	R0008	1
C0018	R0015	0.534
C0019	R0002	1
C0019	R0009	1
C0019	R0015	0.467
C0020	R0002	1
C0020	R0010	1
C0020	R0014	1
C0020	R0015	0.306
C0021	R0002	1

C0021	R0011	1
C0021	R0015	0.707
C0022	R0002	1
C0022	R0012	1
C0022	R0015	0.39
C0023	R0015	1.046
C0024	R0015	0.844
C0025	R0003	1
C0025	R0004	1
C0025	R0013	1
C0025	R0015	0.255
C0026	R0003	1
C0026	R0005	1
C0026	R0015	0.498
C0027	R0003	1
C0027	R0006	1
C0027	R0015	0.791
C0028	R0003	1
C0028	R0007	1
C0028	R0015	0.773
C0029	R0003	1
C0029	R0008	1
C0029	R0015	0.597
C0030	R0003	1
C0030	R0009	1
C0030	R0015	0.716
C0031	R0003	1
C0031	R0010	1
C0031	R0015	0.954
C0032	R0003	1
C0032	R0011	1
C0032	R0013	1
C0032	R0015	0.463
C0033	R0003	1
C0033	R0012	1
C0033	R0015	0.975
C0034	R0015	0.811
C0035	R0015	0.618
C0036	R0015	0.255
C0037	R0004	1
C0037	R0005	1
C0037	R0015	0.244
C0038	R0004	1
C0038	R0006	1
C0038	R0015	0.543

C0039	R0004	1
C0039	R0007	1
C0039	R0015	0.609
C0040	R0004	1
C0040	R0008	1
C0040	R0015	0.359
C0041	R0004	1
C0041	R0009	1
C0041	R0015	0.468
C0042	R0004	1
C0042	R0010	1
C0042	R0015	0.701
C0043	R0004	1
C0043	R0011	1
C0043	R0013	1
C0043	R0015	0.288
C0044	R0004	1
C0044	R0012	1
C0044	R0015	0.72
C0045	R0015	0.588
C0046	R0015	0.455
C0047	R0015	0.498
C0048	R0015	0.244
C0049	R0005	1
C0049	R0006	1
C0049	R0015	0.33
C0050	R0005	1
C0050	R0007	1
C0050	R0015	0.551
C0051	R0005	1
C0051	R0008	1
C0051	R0015	0.156
C0052	R0005	1
C0052	R0009	1
C0052	R0015	0.231
C0053	R0005	1
C0053	R0010	1
C0053	R0015	0.467
C0054	R0005	1
C0054	R0011	1
C0054	R0015	0.255
C0055	R0005	1
C0055	R0012	1
C0055	R0015	0.479
C0056	R0015	0.547

C0057	R0015	0.186
C0058	R0015	0.791
C0059	R0015	0.543
C0060	R0015	0.33
C0061	R0006	1
C0061	R0007	1
C0061	R0014	1
C0061	R0015	0.425
C0062	R0006	1
C0062	R0008	1
C0062	R0015	0.369
C0063	R0006	1
C0063	R0009	1
C0063	R0015	0.285
C0064	R0006	1
C0064	R0010	1
C0064	R0014	1
C0064	R0015	0.185
C0065	R0006	1
C0065	R0011	1
C0065	R0015	0.562
C0066	R0006	1
C0066	R0012	1
C0066	R0015	0.248
C0067	R0015	0.97
C0068	R0015	0.276
C0069	R0015	0.773
C0070	R0015	0.609
C0071	R0015	0.551
C0072	R0015	0.425
C0073	R0007	1
C0073	R0008	1
C0073	R0015	0.681
C0074	R0007	1
C0074	R0009	1
C0074	R0015	0.661
C0075	R0007	1
C0075	R0010	1
C0075	R0015	0.578
C0076	R0007	1
C0076	R0011	1
C0076	R0015	0.798
C0077	R0007	1
C0077	R0012	1
C0077	R0015	0.658

C0078	R0015	0.452
C0079	R0015	0.534
C0080	R0015	0.597
C0081	R0015	0.359
C0082	R0015	0.156
C0083	R0015	0.369
C0084	R0015	0.681
C0085	R0008	1
C0085	R0009	1
C0085	R0015	0.134
C0086	R0008	1
C0086	R0010	1
C0086	R0015	0.448
C0087	R0008	1
C0087	R0011	1
C0087	R0015	0.212
C0088	R0008	1
C0088	R0012	1
C0088	R0015	0.431
C0089	R0015	0.361
C0090	R0015	0.467
C0091	R0015	0.716
C0092	R0015	0.468
C0093	R0015	0.231
C0094	R0015	0.285
C0095	R0015	0.661
C0096	R0015	0.134
C0097	R0009	1
C0097	R0010	1
C0097	R0015	0.324
C0098	R0009	1
C0098	R0011	1
C0098	R0015	0.344
C0099	R0009	1
C0099	R0012	1
C0099	R0015	0.299
C0100	R0015	0.444
C0101	R0015	0.306
C0102	R0015	0.954
C0103	R0015	0.701
C0104	R0015	0.467
C0105	R0015	0.185
C0106	R0015	0.578
C0107	R0015	0.448
C0108	R0015	0.324

C0109	R0010	1
C0109	R0011	1
C0109	R0015	0.659
C0110	R0010	1
C0110	R0012	1
C0110	R0014	1
C0110	R0015	0.088
C0111	R0015	0.605
C0112	R0015	0.707
C0113	R0015	0.463
C0114	R0015	0.288
C0115	R0015	0.255
C0116	R0015	0.562
C0117	R0015	0.798
C0118	R0015	0.212
C0119	R0015	0.344
C0120	R0015	0.659
C0121	R0011	1
C0121	R0012	1
C0121	R0015	0.642
C0122	R0015	0.359
C0123	R0015	0.39
C0124	R0015	0.975
C0125	R0015	0.72
C0126	R0015	0.479
C0127	R0015	0.248
C0128	R0015	0.658
C0129	R0015	0.431
C0130	R0015	0.299
C0131	R0015	0.088
C0132	R0015	0.642

RHS

B	R0001	2
B	R0002	2
B	R0003	2
B	R0004	2
B	R0005	2
B	R0006	2
B	R0007	2
B	R0008	2
B	R0009	2
B	R0010	2
B	R0011	2
B	R0012	2
B	R0013	2

B	R0014	4
BOUNDS		
UP BOUND	C0001	1
UP BOUND	C0002	1
UP BOUND	C0003	1
UP BOUND	C0004	1
UP BOUND	C0005	1
UP BOUND	C0006	1
UP BOUND	C0007	1
UP BOUND	C0008	1
UP BOUND	C0009	1
UP BOUND	C0010	1
UP BOUND	C0011	1
UP BOUND	C0012	1
UP BOUND	C0013	1
UP BOUND	C0014	1
UP BOUND	C0015	1
UP BOUND	C0016	1
UP BOUND	C0017	1
UP BOUND	C0018	1
UP BOUND	C0019	1
UP BOUND	C0020	1
UP BOUND	C0021	1
UP BOUND	C0022	1
UP BOUND	C0023	1
UP BOUND	C0024	1
UP BOUND	C0025	1
UP BOUND	C0026	1
UP BOUND	C0027	1
UP BOUND	C0028	1
UP BOUND	C0029	1
UP BOUND	C0030	1
UP BOUND	C0031	1
UP BOUND	C0032	1
UP BOUND	C0033	1
UP BOUND	C0034	1
UP BOUND	C0035	1
UP BOUND	C0036	1
UP BOUND	C0037	1
UP BOUND	C0038	1
UP BOUND	C0039	1
UP BOUND	C0040	1
UP BOUND	C0041	1
UP BOUND	C0042	1
UP BOUND	C0043	1

UP BOUND	C0044	1
UP BOUND	C0045	1
UP BOUND	C0046	1
UP BOUND	C0047	1
UP BOUND	C0048	1
UP BOUND	C0049	1
UP BOUND	C0050	1
UP BOUND	C0051	1
UP BOUND	C0052	1
UP BOUND	C0053	1
UP BOUND	C0054	1
UP BOUND	C0055	1
UP BOUND	C0056	1
UP BOUND	C0057	1
UP BOUND	C0058	1
UP BOUND	C0059	1
UP BOUND	C0060	1
UP BOUND	C0061	1
UP BOUND	C0062	1
UP BOUND	C0063	1
UP BOUND	C0064	1
UP BOUND	C0065	1
UP BOUND	C0066	1
UP BOUND	C0067	1
UP BOUND	C0068	1
UP BOUND	C0069	1
UP BOUND	C0070	1
UP BOUND	C0071	1
UP BOUND	C0072	1
UP BOUND	C0073	1
UP BOUND	C0074	1
UP BOUND	C0075	1
UP BOUND	C0076	1
UP BOUND	C0077	1
UP BOUND	C0078	1
UP BOUND	C0079	1
UP BOUND	C0080	1
UP BOUND	C0081	1
UP BOUND	C0082	1
UP BOUND	C0083	1
UP BOUND	C0084	1
UP BOUND	C0085	1
UP BOUND	C0086	1
UP BOUND	C0087	1
UP BOUND	C0088	1

UP BOUND	C0089	1
UP BOUND	C0090	1
UP BOUND	C0091	1
UP BOUND	C0092	1
UP BOUND	C0093	1
UP BOUND	C0094	1
UP BOUND	C0095	1
UP BOUND	C0096	1
UP BOUND	C0097	1
UP BOUND	C0098	1
UP BOUND	C0099	1
UP BOUND	C0100	1
UP BOUND	C0101	1
UP BOUND	C0102	1
UP BOUND	C0103	1
UP BOUND	C0104	1
UP BOUND	C0105	1
UP BOUND	C0106	1
UP BOUND	C0107	1
UP BOUND	C0108	1
UP BOUND	C0109	1
UP BOUND	C0110	1
UP BOUND	C0111	1
UP BOUND	C0112	1
UP BOUND	C0113	1
UP BOUND	C0114	1
UP BOUND	C0115	1
UP BOUND	C0116	1
UP BOUND	C0117	1
UP BOUND	C0118	1
UP BOUND	C0119	1
UP BOUND	C0120	1
UP BOUND	C0121	1
UP BOUND	C0122	1
UP BOUND	C0123	1
UP BOUND	C0124	1
UP BOUND	C0125	1
UP BOUND	C0126	1
UP BOUND	C0127	1
UP BOUND	C0128	1
UP BOUND	C0129	1
UP BOUND	C0130	1
UP BOUND	C0131	1
UP BOUND	C0132	1

ENDATA

Listing 8: .col

```
X[1,2]
X[1,3]
X[1,4]
X[1,5]
X[1,6]
X[1,7]
X[1,8]
X[1,9]
X[1,10]
X[1,11]
X[1,12]
X[2,1]
X[2,3]
X[2,4]
X[2,5]
X[2,6]
X[2,7]
X[2,8]
X[2,9]
X[2,10]
X[2,11]
X[2,12]
X[3,1]
X[3,2]
X[3,4]
X[3,5]
X[3,6]
X[3,7]
X[3,8]
X[3,9]
X[3,10]
X[3,11]
X[3,12]
X[4,1]
X[4,2]
X[4,3]
X[4,5]
X[4,6]
X[4,7]
X[4,8]
X[4,9]
X[4,10]
```

X[4,11]
X[4,12]
X[5,1]
X[5,2]
X[5,3]
X[5,4]
X[5,6]
X[5,7]
X[5,8]
X[5,9]
X[5,10]
X[5,11]
X[5,12]
X[6,1]
X[6,2]
X[6,3]
X[6,4]
X[6,5]
X[6,7]
X[6,8]
X[6,9]
X[6,10]
X[6,11]
X[6,12]
X[7,1]
X[7,2]
X[7,3]
X[7,4]
X[7,5]
X[7,6]
X[7,8]
X[7,9]
X[7,10]
X[7,11]
X[7,12]
X[8,1]
X[8,2]
X[8,3]
X[8,4]
X[8,5]
X[8,6]
X[8,7]
X[8,9]
X[8,10]
X[8,11]

X[8,12]
X[9,1]
X[9,2]
X[9,3]
X[9,4]
X[9,5]
X[9,6]
X[9,7]
X[9,8]
X[9,10]
X[9,11]
X[9,12]
X[10,1]
X[10,2]
X[10,3]
X[10,4]
X[10,5]
X[10,6]
X[10,7]
X[10,8]
X[10,9]
X[10,11]
X[10,12]
X[11,1]
X[11,2]
X[11,3]
X[11,4]
X[11,5]
X[11,6]
X[11,7]
X[11,8]
X[11,9]
X[11,10]
X[11,12]
X[12,1]
X[12,2]
X[12,3]
X[12,4]
X[12,5]
X[12,6]
X[12,7]
X[12,8]
X[12,9]
X[12,10]
X[12,11]

Listing 9: .row

```
cc1[1]
cc1[2]
cc1[3]
cc1[4]
cc1[5]
cc1[6]
cc1[7]
cc1[8]
cc1[9]
cc1[10]
cc1[11]
cc1[12]
cc2
cc3
fobj
```

Listing 10: basis.mps

```
* ENCODING=ISO-8859-1
NAME          tsp.mps  Iterations 26  Rows 14  Cols 132
XL C0008      R0001
XL C0009      R0002
XL C0016      R0003
XL C0020      R0004
XL C0032      R0005
XL C0037      R0006
XL C0043      R0007
XL C0051      R0008
XL C0054      R0009
XL C0061      R0010
XL C0064      R0011
XL C0066      R0012
XL C0075      R0013
XL C0087      R0014
UL C0011
UL C0017
UL C0025
UL C0085
UL C0110
ENDATA
```

Listing 11: .sol

```

<?xml version = "1.0" encoding="UTF-8" standalone="yes"?>
<CPLEXSolution version="1.2">
  <header
    problemName="tsp.mps"
    objectiveValue="3.2714999999999996"
    solutionTypeValue="1"
    solutionTypeString="basic"
    solutionStatusValue="1"
    solutionStatusString="optimal"
    solutionMethodString="dual"
    primalFeasible="1"
    dualFeasible="1"
    simplexIterations="26"
    writeLevel="1"/>
  <quality
    epRHS="9.999999999999995e-07"
    epOpt="9.999999999999995e-07"
    maxPrimalInfeas="0"
    maxDualInfeas="0"
    maxPrimalResidual="0"
    maxDualResidual="2.7755575615628914e-17"
    maxX="1"
    maxPi="0.4089999999999997"
    maxSlack="0"
    maxRedCost="1.046"
    kappa="10.5"/>
  <linearConstraints>
    <constraint name="R0001" index="0" status="LL" slack="0" dual="0.27500000000000002"/>
    <constraint name="R0002" index="1" status="LL" slack="0" dual="0.16999999999999998"/>
    <constraint name="R0003" index="2" status="LL" slack="0" dual="0.31950000000000001"/>
    <constraint name="R0004" index="3" status="LL" slack="0" dual="0.14449999999999999"/>
    <constraint name="R0005" index="4" status="LL" slack="0" dual="0.099500000000000005"/>
    <constraint name="R0006" index="5" status="LL" slack="0" dual="0.048999999999999988"/>
    <constraint name="R0007" index="6" status="LL" slack="0" dual="0.40899999999999997"/>
    <constraint name="R0008" index="7" status="LL" slack="0" dual="0.05649999999999995"/>
    <constraint name="R0009" index="8" status="LL" slack="0" dual="0.085999999999999965"/>
    <constraint name="R0010" index="9" status="LL" slack="0" dual="0.16899999999999998"/>
    <constraint name="R0011" index="10" status="LL" slack="0" dual="0.1555"/>
    <constraint name="R0012" index="11" status="LL" slack="0" dual="0.19900000000000001"/>
    <constraint name="R0013" index="12" status="LL" slack="0" dual="-0.012000000000000011"/>
    <constraint name="R0014" index="13" status="LL" slack="0" dual="-0.032999999999999974"/>
  </linearConstraints>
  <variables>
    <variable name="C0001" index="0" status="LL" value="0" reducedCost="0.27799999999999997"/>
    <variable name="C0002" index="1" status="LL" value="0" reducedCost="0.45150000000000001"/>

```

```
<variable name="C0003" index="2" status="LL" value="0" reducedCost="0.3915000000000007"/>
<variable name="C0004" index="3" status="LL" value="0" reducedCost="0.2134999999999994"/>
<variable name="C0005" index="4" status="LL" value="0" reducedCost="0.2230000000000003"/>
<variable name="C0006" index="5" status="LL" value="0" reducedCost="0.2859999999999998"/>
<variable name="C0007" index="6" status="LL" value="0" reducedCost="0.1205"/>
<variable name="C0008" index="7" status="BS" value="1" reducedCost="0"/>
<variable name="C0009" index="8" status="BS" value="0" reducedCost="0"/>
<variable name="C0010" index="9" status="LL" value="0" reducedCost="0.1744999999999996"/>
<variable name="C0011" index="10" status="UL" value="1" reducedCost="-0.1150000000000005"/>
<variable name="C0012" index="11" status="LL" value="0" reducedCost="0.7229999999999998"/>
<variable name="C0013" index="12" status="LL" value="0" reducedCost="0.3544999999999993"/>
<variable name="C0014" index="13" status="LL" value="0" reducedCost="0.3034999999999999"/>
<variable name="C0015" index="14" status="LL" value="0" reducedCost="0.1855000000000003"/>
<variable name="C0016" index="15" status="BS" value="1" reducedCost="0"/>
<variable name="C0017" index="16" status="UL" value="1" reducedCost="-0.2699999999999996"/>
<variable name="C0018" index="17" status="LL" value="0" reducedCost="0.3075000000000005"/>
<variable name="C0019" index="18" status="LL" value="0" reducedCost="0.2110000000000008"/>
<variable name="C0020" index="19" status="BS" value="0" reducedCost="0"/>
<variable name="C0021" index="20" status="LL" value="0" reducedCost="0.3814999999999995"/>
<variable name="C0022" index="21" status="LL" value="0" reducedCost="0.02100000000000019"/>
<variable name="C0023" index="22" status="LL" value="0" reducedCost="1.046"/>
<variable name="C0024" index="23" status="LL" value="0" reducedCost="0.8439999999999997"/>
<variable name="C0025" index="24" status="UL" value="1" reducedCost="-0.1969999999999998"/>
<variable name="C0026" index="25" status="LL" value="0" reducedCost="0.07899999999999987"/>
<variable name="C0027" index="26" status="LL" value="0" reducedCost="0.4225000000000004"/>
<variable name="C0028" index="27" status="LL" value="0" reducedCost="0.0445000000000004"/>
<variable name="C0029" index="28" status="LL" value="0" reducedCost="0.2209999999999997"/>
<variable name="C0030" index="29" status="LL" value="0" reducedCost="0.3105"/>
<variable name="C0031" index="30" status="LL" value="0" reducedCost="0.4654999999999997"/>
<variable name="C0032" index="31" status="BS" value="1" reducedCost="0"/>
<variable name="C0033" index="32" status="LL" value="0" reducedCost="0.4564999999999996"/>
<variable name="C0034" index="33" status="LL" value="0" reducedCost="0.8110000000000005"/>
<variable name="C0035" index="34" status="LL" value="0" reducedCost="0.6179999999999999"/>
<variable name="C0036" index="35" status="LL" value="0" reducedCost="0.255"/>
<variable name="C0037" index="36" status="BS" value="1" reducedCost="0"/>
<variable name="C0038" index="37" status="LL" value="0" reducedCost="0.3495000000000009"/>
<variable name="C0039" index="38" status="LL" value="0" reducedCost="0.05550000000000049"/>
<variable name="C0040" index="39" status="LL" value="0" reducedCost="0.158"/>
<variable name="C0041" index="40" status="LL" value="0" reducedCost="0.2375000000000004"/>
<variable name="C0042" index="41" status="LL" value="0" reducedCost="0.3875000000000001"/>
<variable name="C0043" index="42" status="BS" value="0" reducedCost="0"/>
<variable name="C0044" index="43" status="LL" value="0" reducedCost="0.3765"/>
<variable name="C0045" index="44" status="LL" value="0" reducedCost="0.5879999999999997"/>
<variable name="C0046" index="45" status="LL" value="0" reducedCost="0.4550000000000002"/>
<variable name="C0047" index="46" status="LL" value="0" reducedCost="0.498"/>
```

<variable name="C0048" index="47" status="LL" value="0" reducedCost="0.24399999999999999"/>
<variable name="C0049" index="48" status="LL" value="0" reducedCost="0.18150000000000002"/>
<variable name="C0050" index="49" status="LL" value="0" reducedCost="0.042500000000000038"/>
<variable name="C0051" index="50" status="BS" value="0.5" reducedCost="0"/>
<variable name="C0052" index="51" status="LL" value="0" reducedCost="0.045500000000000004"/>
<variable name="C0053" index="52" status="LL" value="0" reducedCost="0.19850000000000007"/>
<variable name="C0054" index="53" status="BS" value="0.5" reducedCost="0"/>
<variable name="C0055" index="54" status="LL" value="0" reducedCost="0.18049999999999994"/>
<variable name="C0056" index="55" status="LL" value="0" reducedCost="0.547000000000000004"/>
<variable name="C0057" index="56" status="LL" value="0" reducedCost="0.186"/>
<variable name="C0058" index="57" status="LL" value="0" reducedCost="0.791000000000000004"/>
<variable name="C0059" index="58" status="LL" value="0" reducedCost="0.543000000000000004"/>
<variable name="C0060" index="59" status="LL" value="0" reducedCost="0.330000000000000002"/>
<variable name="C0061" index="60" status="BS" value="0.5" reducedCost="0"/>
<variable name="C0062" index="61" status="LL" value="0" reducedCost="0.263500000000000001"/>
<variable name="C0063" index="62" status="LL" value="0" reducedCost="0.150000000000000002"/>
<variable name="C0064" index="63" status="BS" value="0.5" reducedCost="0"/>
<variable name="C0065" index="64" status="LL" value="0" reducedCost="0.357500000000000015"/>
<variable name="C0066" index="65" status="BS" value="0" reducedCost="0"/>
<variable name="C0067" index="66" status="LL" value="0" reducedCost="0.96999999999999997"/>
<variable name="C0068" index="67" status="LL" value="0" reducedCost="0.276000000000000002"/>
<variable name="C0069" index="68" status="LL" value="0" reducedCost="0.773000000000000002"/>
<variable name="C0070" index="69" status="LL" value="0" reducedCost="0.60899999999999999"/>
<variable name="C0071" index="70" status="LL" value="0" reducedCost="0.551000000000000005"/>
<variable name="C0072" index="71" status="LL" value="0" reducedCost="0.42499999999999999"/>
<variable name="C0073" index="72" status="LL" value="0" reducedCost="0.215500000000000008"/>
<variable name="C0074" index="73" status="LL" value="0" reducedCost="0.166000000000000009"/>
<variable name="C0075" index="74" status="BS" value="0.5" reducedCost="0"/>
<variable name="C0076" index="75" status="LL" value="0" reducedCost="0.233500000000000007"/>
<variable name="C0077" index="76" status="LL" value="0" reducedCost="0.050000000000000004"/>
<variable name="C0078" index="77" status="LL" value="0" reducedCost="0.452000000000000001"/>
<variable name="C0079" index="78" status="LL" value="0" reducedCost="0.534000000000000003"/>
<variable name="C0080" index="79" status="LL" value="0" reducedCost="0.59699999999999998"/>
<variable name="C0081" index="80" status="LL" value="0" reducedCost="0.35899999999999999"/>
<variable name="C0082" index="81" status="LL" value="0" reducedCost="0.156"/>
<variable name="C0083" index="82" status="LL" value="0" reducedCost="0.36899999999999999"/>
<variable name="C0084" index="83" status="LL" value="0" reducedCost="0.681000000000000005"/>
<variable name="C0085" index="84" status="UL" value="1" reducedCost="-0.008499999999999952"/>
<variable name="C0086" index="85" status="LL" value="0" reducedCost="0.222500000000000003"/>
<variable name="C0087" index="86" status="BS" value="0.5" reducedCost="0"/>
<variable name="C0088" index="87" status="LL" value="0" reducedCost="0.17549999999999999"/>
<variable name="C0089" index="88" status="LL" value="0" reducedCost="0.36099999999999999"/>
<variable name="C0090" index="89" status="LL" value="0" reducedCost="0.467000000000000003"/>
<variable name="C0091" index="90" status="LL" value="0" reducedCost="0.71599999999999997"/>
<variable name="C0092" index="91" status="LL" value="0" reducedCost="0.468000000000000003"/>

```

<variable name="C0093" index="92" status="LL" value="0" reducedCost="0.2310000000000001"/>
<variable name="C0094" index="93" status="LL" value="0" reducedCost="0.2849999999999998"/>
<variable name="C0095" index="94" status="LL" value="0" reducedCost="0.6610000000000003"/>
<variable name="C0096" index="95" status="LL" value="0" reducedCost="0.1340000000000001"/>
<variable name="C0097" index="96" status="LL" value="0" reducedCost="0.06900000000000061"/>
<variable name="C0098" index="97" status="LL" value="0" reducedCost="0.1025000000000001"/>
<variable name="C0099" index="98" status="LL" value="0" reducedCost="0.01400000000000012"/>
<variable name="C0100" index="99" status="LL" value="0" reducedCost="0.4440000000000001"/>
<variable name="C0101" index="100" status="LL" value="0" reducedCost="0.3059999999999999"/>
<variable name="C0102" index="101" status="LL" value="0" reducedCost="0.9539999999999996"/>
<variable name="C0103" index="102" status="LL" value="0" reducedCost="0.7009999999999996"/>
<variable name="C0104" index="103" status="LL" value="0" reducedCost="0.4670000000000003"/>
<variable name="C0105" index="104" status="LL" value="0" reducedCost="0.185"/>
<variable name="C0106" index="105" status="LL" value="0" reducedCost="0.5779999999999996"/>
<variable name="C0107" index="106" status="LL" value="0" reducedCost="0.4480000000000001"/>
<variable name="C0108" index="107" status="LL" value="0" reducedCost="0.3240000000000001"/>
<variable name="C0109" index="108" status="LL" value="0" reducedCost="0.3345000000000002"/>
<variable name="C0110" index="109" status="UL" value="1" reducedCost="-0.2470000000000005"/>
<variable name="C0111" index="110" status="LL" value="0" reducedCost="0.6049999999999998"/>
<variable name="C0112" index="111" status="LL" value="0" reducedCost="0.7069999999999996"/>
<variable name="C0113" index="112" status="LL" value="0" reducedCost="0.4630000000000002"/>
<variable name="C0114" index="113" status="LL" value="0" reducedCost="0.2879999999999998"/>
<variable name="C0115" index="114" status="LL" value="0" reducedCost="0.255"/>
<variable name="C0116" index="115" status="LL" value="0" reducedCost="0.5620000000000006"/>
<variable name="C0117" index="116" status="LL" value="0" reducedCost="0.7980000000000004"/>
<variable name="C0118" index="117" status="LL" value="0" reducedCost="0.2119999999999999"/>
<variable name="C0119" index="118" status="LL" value="0" reducedCost="0.3439999999999997"/>
<variable name="C0120" index="119" status="LL" value="0" reducedCost="0.6590000000000003"/>
<variable name="C0121" index="120" status="LL" value="0" reducedCost="0.2875000000000003"/>
<variable name="C0122" index="121" status="LL" value="0" reducedCost="0.3589999999999999"/>
<variable name="C0123" index="122" status="LL" value="0" reducedCost="0.3900000000000001"/>
<variable name="C0124" index="123" status="LL" value="0" reducedCost="0.9749999999999998"/>
<variable name="C0125" index="124" status="LL" value="0" reducedCost="0.7199999999999997"/>
<variable name="C0126" index="125" status="LL" value="0" reducedCost="0.4789999999999998"/>
<variable name="C0127" index="126" status="LL" value="0" reducedCost="0.248"/>
<variable name="C0128" index="127" status="LL" value="0" reducedCost="0.6580000000000003"/>
<variable name="C0129" index="128" status="LL" value="0" reducedCost="0.4309999999999999"/>
<variable name="C0130" index="129" status="LL" value="0" reducedCost="0.2989999999999999"/>
<variable name="C0131" index="130" status="LL" value="0" reducedCost="0.08799999999999995"/>
<variable name="C0132" index="131" status="LL" value="0" reducedCost="0.6420000000000002"/>
</variables>
<objectiveValues>
  <objective index="0" name="R0015" value="3.2714999999999996"/>
</objectiveValues>
</CPLEXSolution>

```


References

- [1] Laurence A. Wolsey, George L. Nemhauser, *Integer and Combinatorial Optimization*.
- [2] IBM, *IBM ILOG CPLEX Optimization Studio CPLEX User's Manual*