



# Computer Programming Language Solution to a Transportation Problem Involving a Concave Cost Function

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#### Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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## Abstract

The work is on computer programming language solution to a transportation problem involving a concave cost function. Two computer programming languages; Wolfram Mathematica and Anaconda Python programming tools were employed in this study to effectively solve four real life examples from published works. The results from the programming languages yielded an optimal value of ₦253,000 with an optimal solution as  $z_{12} = 13$ ,  $z_{22} = 5$ ,  $z_{23} = 8$ ,  $z_{31} = 11$  and  $z_{33} = 4$  in the first example and the remaining three examples were successfully solved with optimal values of ₦377,000, GH¢ 236,000 and ₦509,000 respectively, and the results agreed with the results of existing Karush-Kuhn-Tucker (KKT) procedure of Modified Distribution Method.

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## 1 Introduction

“Transportation problems involving a concave cost function, simply means a nonlinear transportation problem; indicating a scenario whereby volume discounts are being available for bulk shipments. In this case, the cost function of the transportation problem is separable, and the marginal cost (cost per unit of goods shipped) decreases as the shipment volume increases, so it generally assumes a concave structure. It increases due to the increase in the total cost per additional unit of goods shipped” [1]. Discounts may be directly related to the unit of commodity or may have the same rate for a particular amount. Thus, the discount may be either directly associated to the unit commodity or have the equivalent rate for some quantity. However, if the discount is directly associated to the unit commodity, then the resulting cost function becomes continuous and possesses continuous first partial derivatives.

“Profit and cost is what virtually everyone deems interested in employing, using any efficient resources to optimize; hence various forms of transportation models are in existence. There are different kinds of transportation problems which are applied in the business world and the primary aim of a transportation problem is to find a means of moving this transfer of goods at a minimized total cost in order to make profit” [2,3]. In describing the transportation problem in its conventional form, the assumption is that an informed decision maker has an understanding on the value of transportation cost, demand and supply; hence, unpredictability is a common occurrence in real life circumstances.

This study tackles a transportation problem in a concave cost function using computer programming languages. However, there are some factors that are responsible for the cost of goods, and some of them are transport, raw materials' costs and labour. This implies that the cost of raw materials is directly proportional to the cost of the goods, and the pricing system is also affected when there is a significant variation in the transportation cost [4]. The cost of goods per unit shipped is assumed to be constant irrespective of the quantity shipped from a given source to a defined destination; but the cost sometimes may not be constant in actuality. Sometimes, quantity discounts are feasible for large shipments in such a way that the marginal cost of transporting a unit might approach a specific pattern [5].

## 2 Literature Review

Oliveira et al. [6] carried out “a research on a comparative study of linear programming and nonlinear programming models of the ship speed optimisation problem in maritime transportation”. It was demonstrated in the work reported in the study that the linear programming formulation yielded better results than the nonlinear programming formulation for the ship speed optimisation problem. Therefore, great care must be taken in using the uniform speed assumption, in view of the complex nature of the functional relation between ship fuel consumption rate and ship speed, as pointed out by Psarftis & Kontovas [7]. In view of the findings summarised in the work, the linear programming formulation of the ship speed optimisation problem holds many promises that worth exploring in further research. These include complex functional relations between ship fuel consumption and ship speed to take into account dependence on ship payload and weather conditions encountered in ship voyages, ship routing in both liner and tramp shipping, and ship fuel bunkering.

Amaravathy et al. [8] compared the existing methods with the one they worked on the optimum solution of Origin, First, Second, Third, and Fourth quadrants (OFSTF) and Maximum Divide Minimum Allotment (MDMA) methods. In their study, different approaches to the OFSTF method (origin, first, second, third, fourth quadrants) were used to directly obtain a practical solution to the transport problem. The proposed method was unique and always provided a practical (probably optimal) solution without disturbing the state of degeneration. This process involved a minimum of iterations to achieve the optimization. In order to confirm the validity of the proposed method, they solved numerical examples and discussed the degeneracy problem.

### 3 Transportation Problem via Concave Cost Functions

“Volume discounts may be available for bulk shipments. In this case, the cost function of the transportation problem is separable, and the marginal cost (cost per unit of goods shipped) decreases as the shipment volume increases, so shipping cost generally assumes a concave structure. It increases due to the increase in the total cost per additional unit of goods shipped” [1]. However, If the discount is directly associated to the unit commodity, then the resulting cost function becomes continues and possesses continues first partial derivatives.

### 4 Computer Written Programming Codes for Transportation Problem in a Concave Cost Function

This section explains how the transportation problem in a concave cost function could be solved using two programming languages codes written in Wolfram Mathematica programming and Anaconda Python programming.

#### 4.1 Wolfram mathematica computer written programming codes for transportation problem in a concave cost function

```

Clear[f2, z, k, R, C, L, K, V, a];
m=p (Number of sources);
n=q (Number of destinations);
f2[z_]:=k11*z[1,1]-p11*z[1,1]^2+k12*z[1,2]-p12*z[1,2]^2+...+k1j*z[1,j]-p1j*z[1,j]^2+...+
k1n*z[1,n]-p1n*z[1,n]^2+k21*z[2,1]-p21*z[2,1]^2+k22*z[2,2]-p22*z[2,2]^2+k2j*z[2,j]-p2j*z[2,j]^2+...
k2n*z[2,n]-p2n*z[2,n]^2+...+ki1*z[i,1]-pi1*z[i,1]^2+ki2*z[i,2]-pi2*z[i,2]^2+...+kij*z[i,j]-
pij*z[i,j]^2+...+kin*z[i,n]-pin*z[i,n]^2+...+km1*z[m,1]-pm1*z[m,1]^2+km2*z[m,2]-pm2*z[m,2]^2+...
kmj*z[m,j]-pmj*z[m,j]^2+...+kmn*z[m,n]-pmn*z[m,n]^2;
R1:=z[1,1]+z[1,2]+...+z[1,j]+...+z[1,n]==S1;
R2:=z[2,1]+z[2,2]+...+z[2,j]+...+z[2,n]==S2;
⋮ ⋮ ⋮ ⋮
Ri:=z[i,1]+z[i,2]+...+z[i,j]+...+z[i,n]==Si;
⋮ ⋮ ⋮ ⋮
Rm:=z[m,1]+z[m,2]+...+z[m,j]+...+z[m,n]==Sm;
C1:=z[1,1]+z[2,1]+...+z[i,1]+...+z[m,1]==D1;
C2:=z[1,2]+z[2,2]+...+z[i,2]+...+z[m,2]==D2;
⋮ ⋮ ⋮ ⋮
Cj:=z[1,j]+z[2,j]+...+z[i,j]+...+z[m,j]==Dj;
⋮ ⋮ ⋮ ⋮
Cn:=z[1,n]+z[2,n]+...+z[i,n]+...+z[m,n]==Dn;
L=Join[{R1},{R2},...,{Ri},...,{Rm},{C1},{C2},...,{Cj},...,{Cn}];
K1:=z[1,1]>=0;
K2:=z[1,2]>=0;
⋮ ⋮
K3:=z[1,j]>=0;
⋮ ⋮
K4:=z[1,n]>=0;
K5:=z[2,1]>=0;
K6:=z[2,2]>=0;
⋮ ⋮
K7:=z[2,j]>=0;
⋮ ⋮
K8:=z[2,n]>=0;
⋮ ⋮
K9:=z[i,1]>=0;

```

```

K10:=z[i,2]>=0;
⋮
⋮
K11:=z[i,j]>=0;
⋮
⋮
K12:=z[i,n]>=0;
⋮
⋮
K13:=z[m,1]>=0;
K14:=z[m,2]>=0;
⋮
⋮
K15:=z[m,j]>=0;
⋮
⋮
K16:=z[m,n]>=0;
K=Join[{K1},{K2},...,{K3},...,{K4},{K5},{K6},...,{K7},...,{K8},...,{K9},{K10},...,{K11},...,{K12},...,{K13},{K14},...,{K15},...,{K16}];
V=Join[L,K];
a=Variables[f2[z]];
tim=Timing[NMinimize[{f2[z],V},a,StepMonitor:› Print["Step: z[1,1],z[1,2],z[1,3],z[3,3] =
","z[1,1]",",z[1,2]",",z[1,3]",",z[3,3]]]];
tim

```

## 4.2 Anaconda python computer written programming codes for transportation problem in a concave case

```
In [1]: from gekko import GEKKO
import numpy as np
from matplotlib import pyplot as plt
```

```
In [2]: # Initialize Model
m = GEKKO(remote = True)
```

```
In [3]: # help (m)
# define parameters
eq_1 = m.Param(value = S1)
eq_2 = m.Param(value = S2)
⋮
⋮
eq_i = m.Param(value = Si)
⋮
⋮
eq_m = m.Param(value = Sm)
eq_m+1 = m.Param(value = D1)
eq_m+2 = m.Param(value = D2)
⋮
⋮
eq_j = m.Param(value = Dj)
⋮
⋮
eq_n = m.Param(value = Dn)
```

```
In [4]: # Initialize variables, k=number of variables
z11, ..., z1j, ..., z1n, z21, ..., z2j, z2n, ..., z1l, z12, ..., z1j, ..., zin, ..., zm1, zm2, ..., \ zmj, ..., zmn=
[m.Var() for i in range(k)]
```

```
In [5]: # Initialize values (Assigning values or constants whose summation is less than or equal to Si or Dj)
z11 = m.Var(value = c1)
⋮
⋮
z1j = m.Var(value = c2)
⋮
⋮
z1n = m.Var(value = c3)
z21 = m.Var(value = c4)
```

```

        :
        :
z2j = m.Var(value = c5)
z2n = m.Var(value = c6)
        :
        :
zi1 = m.Var(value = c7)
zi2 = m.Var(value = c8)
        :
        :
zij = m.Var(value = c9)
        :
        :
zin = m.Var(value = c10)
        :
        :
Zm1 = m.Var(value = c11)
Zm2 = m.Var(value = c12)
        :
        :
Zmj = m.Var(value = c13)
        :
        :
Zmn = m.Var(value = c14)
```

In [6]:

```

z11.lower = 0
        :
        :
z1j.lower = 0
        :
        :
z1n.lower = 0
z21.lower = 0
        :
        :
z2j.lower = 0
z2n.lower = 0
        :
        :
zi1.lower = 0
zi2.lower = 0
        :
        :
zij.lower = 0
        :
        :
zin.lower = 0
        :
        :
Zm1.lower = 0
Zm2.lower = 0
zmj.lower = 0
        :
        :
Zmn.lower = 0
```

In [7]:

```

z11.upper = None
        :
        :
z1j.upper = None
        :
        :
z1n.upper = None
z21.upper = None
        :
        :
z2j.upper = None
z2n.upper = None
        :
        :
zi1.upper = None
zi2.upper = None
```

```

    :
    :
zij.upper = None
    :
    :
zin.upper = None
    :
    :
Zm1.upper = None
Zm2.upper = None
zmj.upper = None
    :
    :
Zmn.upper = None
```

In [8]: m.Equations([z11+z12+...+z1j+...+z1n == eq\_1,..., zi1+zi2+zij+...+zin == eq\_i,\n...,zm1+zm2+...+zmj+...+zmn == eq\_m, z11+z21+...+zi1+...+zm1 == eq\_m+1 \n...,z1j+z2j+...+zij+...+zmj == eq\_j,..., z1n+z2n+...+zin+...+zmn == eq\_n])

In [9]: m.Obj(k<sub>11</sub>\*z11 - p<sub>11</sub>\*z11\*\*2 + k<sub>12</sub>\*z12 - p<sub>12</sub>\*z12\*\*2 + ... + k<sub>1j</sub>\*z1j - p<sub>1j</sub>\*z1j\*\*2 + ... +\n k<sub>1n</sub>\*z1n - p<sub>1n</sub>\*z1n\*\*2 + k<sub>21</sub>\*z21 - p<sub>21</sub>\*z21\*\*2 + k<sub>22</sub>\*z22 - p<sub>22</sub>\*z22\*\*2 + k<sub>2j</sub>\*z2j - p<sub>2j</sub>\*z2j\*\*2 + ... + k<sub>2n</sub>\*z2n -\n p<sub>2n</sub>\*z2n\*\*2 + ... + k<sub>ij</sub>\*zij - p<sub>ij</sub>\*zij\*\*2 + k<sub>ij</sub>\*zij - p<sub>ij</sub>\*zij\*\*2 + ... + k<sub>in</sub>\*zin -\n p<sub>in</sub>\*zin\*\*2 + ... + k<sub>m1</sub>\*zm1 - p<sub>m1</sub>\*zm1\*\*2 + k<sub>m2</sub>\*zm2 - p<sub>m2</sub>\*zm2\*\*2 + ... + k<sub>mj</sub>\*zmj - p<sub>mj</sub>\*zmj\*\*2 + ... + k<sub>mn</sub>\*zmn\n - p<sub>mn</sub>\*zmn\*\*2)

In [10]: m.options.IMODE=3

**In [11]: m.solve(GEKKO(remote=True))**

In [12]: m.options.SOLVER=1

In [12]: m.options.SOLVER=1

```

In [13]: print()
print('Results')
print('z11: ' + str(z11.value))
    :
    :
print('z1j: ' + str(z1j.value))
    :
    :
print('z1n: ' + str(z1n.value))
print('z21: ' + str(z21.value))
    :
    :
print('z2j: ' + str(z2j.value))
print('z2n: ' + str(z2n.value))
    :
    :
print('zi1: ' + str(zi1.value))
print('zi2: ' + str(zi2.value))
    :
    :
print('zij: ' + str(zij.value))
    :
    :
print('zin: ' + str(zin.value))
    :
    :
print('zm1: ' + str(zm1.value))
print('zm2: ' + str(zm2.value))
print('zmj: ' + str(zmj.value))
    :
    :
print('zmn: ' + str(zmn.value))
```

Results

## 5 Numerical Problems

### 5.1 Example 1

Unilever Nigeria Plc located in Apapa Ikeja, produces and sells the products as indicated in the Table 1 together with the associated company's percentage discount:

**Table 1. Unit cost of products and company's percentage discount**

Markets segments			Supply
P	Q	R	
Omo washing powder	5	4	6
Blue Band margarine	7	6	5
Vaseline	9	11	8
DEMAND	11,000	18,000	12,000
Company's percentage discount shipped			
P	Q	R	
Omo washing powder	0.03	0.015	0.04
Blue Band margarine	0.02	0.03	0.05
Vaseline	0.035	0.05	0.03

Source: Okenwe [12]

Due to the discount given to each box as a result of large volume of transporting from source  $i$  to destination  $j$ , the formulation of the transportation problem in nonlinear form is:

$$\text{Min.} \sum_{i=1}^3 \sum_{j=1}^3 k_{ij} z_{ij}$$

$$\text{S.t. } z_{11} + z_{12} + z_{13} = 13$$

$$z_{21} + z_{22} + z_{23} = 13$$

$$z_{31} + z_{32} + z_{33} = 15$$

$$z_{11} + z_{21} + z_{31} = 11$$

$$z_{12} + z_{22} + z_{32} = 18$$

$$z_{13} + z_{23} + z_{33} = 12$$

Where

$$k_{11}z_{11} = 5z_{11} - p_{11}z_{11}^2, k_{12}z_{12} = 4z_{12} - p_{12}z_{12}^2, k_{13}z_{13} = 6z_{13} - p_{13}z_{13}^2, k_{21}z_{21} = 7z_{21} - p_{21}z_{21}^2$$

$$k_{22}z_{22} = 6z_{22} - p_{22}z_{22}^2, k_{23}z_{23} = 5z_{23} - p_{23}z_{23}^2, k_{31}z_{31} = 9z_{31} - p_{31}z_{31}^2, k_{32}z_{32} = 11z_{32} - p_{32}z_{32}^2$$

$$k_{33}z_{33} = 8z_{33} - p_{33}z_{33}^2$$

Due to the discount given to each box as a result of large volume of transporting from source  $i$  to destination  $j$ , then the cost function ( $k_{ij}$ ) is indicated as:

$$k_{11}z_{11} = 5z_{11} - 0.03z_{11}^2, k_{12}z_{12} = 4z_{12} - 0.015z_{12}^2, k_{13}z_{13} = 6z_{13} - 0.04z_{13}^2, k_{21}z_{21} = 7z_{21} - 0.02z_{21}^2$$

$$k_{22}z_{22} = 6z_{22} - 0.03z_{22}^2, k_{23}z_{23} = 5z_{23} - 0.05z_{23}^2, k_{31}z_{31} = 9z_{31} - 0.035z_{31}^2, k_{32}z_{32} = 11z_{32} - 0.05z_{32}^2$$

$$k_{33}z_{33} = 8z_{33} - 0.03z_{33}^2$$

The output of Example 1 via Wolfram Mathematica and Anaconda Python is shown below;

### 5.1.1 Wolfram mathematica output of example 1

Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0520463, 12.9405, 0.00746324, 0.00716501$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0520463, 12.9405, 0.00746324, 0.00716501$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0614247, 12.9315, 0.0070737, 0.00427768$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0614247, 12.9315, 0.0070737, 0.00427768$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0614247, 12.9315, 0.0070737, 0.00427768$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0505677, 12.9469, 0.00255937, 0.000755734$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.09301, 12.8942, 0.0128178, 0.00827994$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0827176, 12.9154, 0.00191623, 0.000232425$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0827176, 12.9154, 0.00191623, 0.000232425$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.121709, 12.8703, 0.00795573, -0.00110205$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.196778, 12.7822, 0.0210317, 0.00454851$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.196778, 12.7822, 0.0210317, 0.00454851$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.207363, 12.7865, 0.00613269, -0.000462094$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.334976, 12.6352, 0.0298175, -0.000108529$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.334976, 12.6352, 0.0298175, -0.000108529$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.510508, 12.4472, 0.0422997, 0.120491$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.488911, 12.4803, 0.0307975, 0.0812445$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.462777, 12.5068, 0.0303988, 0.0465901$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.451278, 12.5173, 0.0314083, -0.00130412$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.451278, 12.5173, 0.0314083, -0.00130412$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.454816, 12.52, 0.0251821, 0.0191165$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.454419, 12.5258, 0.0197449, 0.0185168$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.454419, 12.5258, 0.0197449, 0.0185168$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.454419, 12.5258, 0.0197449, 0.0185168$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.445135, 12.5355, 0.0193661, 0.00427392$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.441966, 12.541, 0.0170058, 0.00261565$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.441447, 12.5459, 0.0126755, 0.00311075$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.437815, 12.5501, 0.012064, 0.0000337962$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.437815, 12.5501, 0.012064, 0.0000337962$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.441787, 12.5518, 0.00639919, 0.00902117$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.436281, 12.5617, 0.00201731, 0.00303067$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.436281, 12.5617, 0.00201731, 0.00303067$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.436281, 12.5617, 0.00201731, 0.00303067$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.442416, 12.5576, 0.0111263$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.437073, 12.5629, 0.0029804$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.437073, 12.5629, 0.0029804$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.437073, 12.5629, 0.0029804$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.438726, 12.5613, 0.001833$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.439106, 12.5609, 0.0000126832$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.446625, 12.5534, 0.00368506$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.446625, 12.5534, 0.00368506$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = -1.08549, 14.0855, 0.00451078$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.131384, 12.8686, 0. -0.00737012$   
 Step :  $z[1,1],z[1,2],z[1,3],z[3,3] = 0.0027845, 12.9972, 0. -0.0015764$

```

Step : z[1,1],z[1,2],z[1,3],z[3,3] = 3.05114*10-6 , 13. , 0. -0.0000134125
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 2.379*10-12 , 13. , 0. -1.56092*10-11
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 1.19982*10-23 , 13. , 0. 0.
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0.446625 , 12.5524 , 0.001 , 0.00368506
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0.588814 , 12.4074 , 0.00376971 , 0.995278
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0.00588814 , 12.8423 , 0.151809 , 1.52872
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0.0251432 , 12.9023 , 0.0725069 , 1.84993
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0.0211205 , 12.9227 , 0.0562188 , 3.17547
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0.0121676 , 12.9687 , 0.0191761 , 4.08295
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0.000229113 , 12.9993 , 0.000433091 , 4.00134
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 2.30458*10-6 , 13. , 4.41297*10-6 , 4.00001
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.69684
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.92754
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.98208
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.99553
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.99888
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.99972
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.99993
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 3.99998
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 4.
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 4.
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 4.
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 4.
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 4.
Step : z[1,1],z[1,2],z[1,3],z[3,3] = 0. 13. , 0. 4.
tim
{6.09964,{z[1,1]->0.,z[1,2]->13.,z[1,3]->0.,z[2,1]->0.,z[2,2]->5.,z[2,3]->8.,z[3,1]->11.,z[3,2]->9.24835*10-8,z[3,3]->4.}}}
Clear[f,fmin]
f2[z]=5*z[1,1]+4*z[1,2]+6*z[1,3]+7*z[2,1]+6*z[2,2]+5*z[2,3]+9*z[3,1]+11*z[3,2]+8*z[3,3];
z[1,1]=0;
z[1,2]=13;
z[1,3]=0;
z[2,1]=0;
z[2,2]=5;
z[2,3]=8;
z[3,1]=11;
z[3,2]=0;
z[3,3]=4;
fmin=f2[z];
fmin
253

```

## 5.1.2 Anaconda python output of example 1

```

In [1]: from gekko import GEKKO
        import numpy as np
        from matplotlib import pyplot as plt
In [2]: # Initialize Model
        m = GEKKO(remote = True)
In [3]: # help(m)
        # define parameters
        eq_1 = m.Param(value =13)
        eq_2 = m.Param(value =15)
        eq_3 = m.Param(value =11)
        eq_4 = m.Param(value =18)
        eq_5 = m.Param(value =12)
In [4]: # Initialize variables
        z11, z12, z13, z21, z22, z23, z31, z32, z33 = \
        [m.Var() for i in range(9)]
In [5]: # Initialize values
        z11 = m.Var(value = 1)
        z12 = m.Var(value = 2)
        z13 = m.Var(value = 3)
        z21 = m.Var(value = 2)
        z22 = m.Var(value = 2)
        z23 = m.Var(value = 5)

```

```

z31 = m.Var(value = 1)
z32 = m.Var(value = 5)
z33 = m.Var(value = 4)
In [6]: z11.lower = 0
z12.lower = 0
z13.lower = 0
z21.lower = 0
z22.lower = 0
z23.lower = 0
z31.lower = 0
z32.lower = 0
z33.lower = 0
In [7]: z11.upper = None
z12.upper = None
z13.upper = None
z21.upper = None
z22.upper = None
z23.upper = None
z31.upper = None
z32.upper = None
z33.upper = None
In [8]: m.Equations([z11+z12+z13 == eq_1, z21+z22+z23 == eq_1, z31+z32+z33 == eq_2,\ z11+z21+z31 == eq_3,
z12+z22+z32 == eq_4, z13+z23+z33 == eq_5])
Out [8]: [<gekko.gekko.EquationObj at 0x237ff8d28e0>,
<gekko.gekko.EquationObj at 0x237ff8d2c10>,
<gekko.gekko.EquationObj at 0x237ff8d29d0>,
<gekko.gekko.EquationObj at 0x237ff8cbbb0>,
<gekko.gekko.EquationObj at 0x237814de4f0>,
<gekko.gekko.EquationObj at 0x237ff8db670>]
In [9]: m.Obj(5*z11-0.03*z11**2+4*z12-0.015*z12**2+4*z13-0.04*z13**2+7*z21-0.02*z21**2\
+6*z22-0.03*z22**2+5*z23-0.05*z23**2+9*z31-0.035*z31**2+11*z32-0.05*z32**2\
+8*z33-0.03*z33**2)
In [10]: m.options.IMODE =3

In [11]: m.solve(GEKKO(remote=True))
apm 105.112.210.32_gk_model0 <br><pre> -----
APMonitor, Version 1.0.1
APMonitor Optimization Suite
-----
----- APM Model Size -----
Each time step contains
Objects : 0
Constants : 0
Variables : 32
Intermediates: 0
Connections : 0
Equations : 7
Residuals : 7

Number of state variables: 27
Number of total equations: - 6
Number of slack variables: - 0
-----
Degrees of freedom : 21

iter objective inf_pr inf_du lg(mu) ||d|| lg(rg) alpha_du alpha_pr ls
0 1.6833500e+02 9.00e+00 2.67e+00 0.0 0.00e+00 - 0.00e+00 0.00e+00 0
1 1.6881766e+02 7.90e+00 3.00e+00 -6.0 1.46e+01 -4.0 6.36e-02 1.23e-01h 1
2 2.4765788e+02 1.44e+00 2.39e+00 0.4 4.05e+00 -4.5 4.61e-01 8.18e-01h 1
3 2.4037967e+02 1.36e+00 2.09e+00 -0.9 6.08e+01 -1.3 8.77e-02 5.61e-02f 1
4 2.3932635e+02 8.82e-01 4.17e+00 -1.1 5.78e+00 -1.8 1.34e-01 3.49e-01h 1
5 2.4058508e+02 5.94e-01 2.85e+00 -1.9 2.08e+00 -2.3 6.35e-01 3.27e-01h 1
6 2.3850071e+02 3.49e-01 2.45e+00 -6.6 5.01e+00 -2.8 3.07e-03 4.12e-01h 1

```

```

7 2.4183230e+02 1.17e-02 1.84e-01 -1.2 2.34e-01 -3.3 1.00e+00 9.66e-01h 1
8 2.4180281e+02 2.53e-06 2.48e-04 -3.0 5.00e-02 -3.7 9.98e-01 1.00e+00h 1
9 2.4180001e+02 4.97e-09 2.36e-07 -9.0 4.96e-04 -4.2 9.98e-01 9.98e-01h 1
iter objective inf_pr inf_du lg(mu) ||d|| lg(rg) alpha_du alpha_pr ls
10 2.4180000e+02 3.55e-15 1.82e-11 -11.0 8.74e-07 -4.7 1.00e+00 1.00e+00h 1

```

Number of Iterations....: 10

(scaled) (unscaled)

```

Objective.....: 2.4179999978554039e+02 2.4179999978554039e+02
Dual infeasibility.....: 1.8188284627939566e-11 1.8188284627939566e-11
Constraint violation....: 3.5527136788005009e-15 3.5527136788005009e-15
Complementarity.....: 1.1361390269409665e-11 1.1361390269409665e-11
Overall NLP error.....: 1.8188284627939566e-11 1.8188284627939566e-11

```

Number of objective function evaluations = 11

Number of objective gradient evaluations = 11

Number of equality constraint evaluations = 11

Number of inequality constraint evaluations = 0

Number of equality constraint Jacobian evaluations = 11

Number of inequality constraint Jacobian evaluations = 0

Number of Lagrangian Hessian evaluations = 10

Total CPU secs in IPOPT (w/o function evaluations) = 0.006

Total CPU secs in NLP function evaluations = 0.001

EXIT: Optimal Solution Found.

The solution was found.

The final value of the objective function is 241.799999785540

---

```

Solver : IPOPT (v3.12)
Solution time : 1.44999999022111E-002 sec
Objective : 241.800000645399
Successful solution

```

---

```

In [12]: m.options.SOLVER=1
In [13]: print(")
print('Results')
print('z11: ' + str(z11.value))
print('z12: ' + str(z12.value))
print('z13: ' + str(z13.value))
print('z21: ' + str(z21.value))
print('z22: ' + str(z22.value))
print('z23: ' + str(z23.value))
print('z31: ' + str(z31.value))
print('z32: ' + str(z32.value))
print('z33: ' + str(z33.value))
Results
z11: [0.0]
z12: [13.00000004]
z13: [0.0]
z21: [0.0]
z22: [5.00000001]
z23: [8.00000001]
z31: [11.00000003]
z32: [0.0]
z33: [4.00000002]

```

Examples 2, 3 and 4 were extracted from Osuji et al. [9], Abdul-Salam [10] and Opara et al. [11] respectively, solved via the same procedure as displayed in Example 1, and their results are presented in Table 2, along with the results of others.

**Table 2. Summary of results for the four practical examples used**

<b>Example 1</b>	Wolfram Mathematica Optimal Solution Anaconda Python Optimal Solution <b>Optimal Value</b>	$z_{12} = 13, z_{22} = 5, z_{23} = 8, z_{31} = 11, z_{33} = 4$ $z_{12} = 13, z_{22} = 5, z_{23} = 8, z_{31} = 11, z_{33} = 4$ <b>253,000</b>
<b>Example 2</b>	Wolfram Mathematica Optimal Solution Anaconda Python Optimal Solution <b>Optimal Value</b>	$z_{14} = 5, z_{15} = 6, z_{22} = 7, z_{23} = 9, z_{25} = 1, z_{31} = 6, z_{34} = 5$ $z_{14} = 5, z_{15} = 6, z_{22} = 7, z_{23} = 9, z_{25} = 1, z_{31} = 6, z_{34} = 5$ <b>377,000</b>
<b>Example 3</b>	Wolfram Mathematica Optimal Solution Anaconda Python Optimal Solution <b>Optimal Value</b>	$z_{12} = 7, z_{13} = 8, z_{21} = 10, z_{22} = 3, z_{24} = 12, z_{31} = 10$ $z_{12} = 7, z_{13} = 8, z_{21} = 10, z_{22} = 3, z_{24} = 12, z_{31} = 10$ <b>236,000</b>
<b>Example 4</b>	Wolfram Mathematica Optimal Solution Anaconda Python Optimal Solution <b>Optimal Value</b>	$z_{12} = 8, z_{15} = 5, z_{23} = 12, z_{25} = 4, z_{31} = 9, z_{32} = 2, z_{41} = 1, z_{44} = 14$ $z_{12} = 8, z_{15} = 5, z_{23} = 12, z_{25} = 4, z_{31} = 9, z_{32} = 2, z_{41} = 1, z_{44} = 14$ <b>509,000</b>

## 6 Conclusion

The study employed computer programming languages to solve transportation problem in a concave function. Four real life examples extracted from different authors of published works were employed successfully to demonstrate the effectiveness of the written programmes. The output from the two programming languages is the same for optimal solution.

## Competing Interests

Authors have declared that no competing interests exist.

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