KTH ROYAL INSTITUTE OF TECHNOLOGY

SF2863 Systems Engineering

Home Assignment 2

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Marginal Allocation

- (1) There are four different requirements that must be met in order to apply the marginal allocation algorithm:
 - The objective functions are separable.
 - The objective functions are integer-convex.
 - One objective functions is increasing.
 - One objective functions is decreasing.

The two objective functions for this problem are defined as:

$$f = \mathbf{c}^{\mathsf{T}} \mathbf{s}$$
$$g = EBO(\mathbf{s})$$

where.

 X_i = Number of LRU_i in workshop

 s_i = Number of spare part units

EBO = Expected number of back-orders for every LRU

 c_i = Costs for spare units

 $\mathbf{c}^{\mathsf{T}}\mathbf{s}$ = Increasing objective function

 $EBO(\mathbf{s}) = Decreasing objective function$

The EBO can be written as the sum of the expected number of back-orders due to shortage of each LRU in the following manner

$$EBO(\mathbf{s}) = \sum_{i=1}^{9} EBO_i(s_i)$$

The objective function g is thus separable. The total cost due to purchase of LRUs, $\mathbf{c}^{\intercal}\mathbf{s}$, can similarly be written as the sum of the individual costs for each LRU

$$\mathbf{c}^{\mathsf{T}}\mathbf{s} = \sum_{i=1}^{9} c_i s_i$$

So f is separable as well. It is apparent from the definitions above that with each increasing s_i , g decreases and f increases, so all four requirements are met and the marginal allocation method is applicable to solve this problem.

- (2) The marginal allocation algorithm was implemented as described in "On spare parts optimization" by Krister Svanberg and was initiated with no spares. The development of the EBO when adding each new spare LRU unit was then calculated.
- (3) The marginal allocation algorithm returned the efficient curve for the problem as presented in Figure 1. The cost, EBO, purchase strategy and the marginal decrease in EBO for each new unit of cost spent on the LRUs is shown in Table 1.

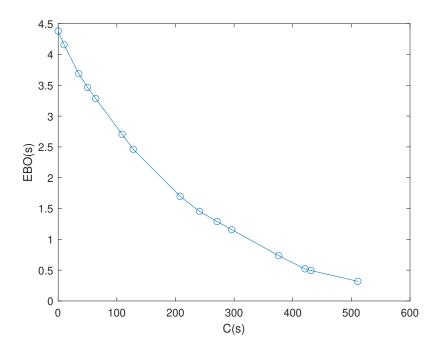


Figure 1: Efficient curve according to marginal allocation

Table 1: Efficient solutions

| Cost | EBO | ΔEBO | P1 | P2 | Р3 | P4 | P5 | P6 | P7 | P8 | P9 |
|------|--------|--------------|----|----|----|----|----|----|----|----|----|
| 0 | 4.3790 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 4.1578 | 0.2212 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 35 | 3.6904 | 0.4674 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 50 | 3.4653 | 0.2251 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 64 | 3.2840 | 0.1813 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 109 | 2.7055 | 0.5785 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 128 | 2.4613 | 0.2442 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 208 | 1.6982 | 0.7631 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| 241 | 1.4540 | 0.2442 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 271 | 1.2893 | 0.1647 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 296 | 1.1574 | 0.1319 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 1 |
| 376 | 0.7355 | 0.4219 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 1 | 1 |
| 421 | 0.5211 | 0.2144 | 1 | 1 | 2 | 1 | 1 | 2 | 2 | 1 | 1 |
| 431 | 0.4946 | 0.0265 | 1 | 1 | 2 | 1 | 2 | 2 | 2 | 1 | 1 |
| 511 | 0.3184 | 0.1762 | 1 | 1 | 2 | 1 | 2 | 2 | 3 | 1 | 1 |

Dynamic Programming

- (4) In this case the problem will be solved using a dynamic programming approach instead. The notation for the problem setup is as follows
 - States, \mathbf{s}_n : The available inventory of parts at the start of each stage.
 - Stages, n: Possible available budgets, $n = 0, 1, \dots, 500$.
 - Decisions, x_n : Which part (P1, P2, ..., P9) should be purchased at each stage n and added to the inventory.
 - State-update EQ: $s_{n+1} = s_n + x_n$
 - Value functions: $f_n^*(s_n) = \min\{f_n(s_n, x_n)\} = \min\{EBO(s_n, x_n)\}$
 - Recursive relation: $f_n^*(s_n) = \min\{f_{n+1}(s_n, x_n) + \sum_{k=1}^{Budget/c(i)} G(s_k, x_k)\}$

The recursive relation are returning the optimal solution using $EBO(k*\#parts) + EBO(current\ budget - k*\#parts)$

The fundamental process of the dynamic programming algorithm is as follows

```
Algorithm 1 Dynamic Programming
```

```
1: for Every budget do

⊳ Setup before recursion

 2:
      for Every part do
          Create matrix with how many parts we can purchase using budget
 3:
 4:
      end for
 5: end for
 6: for Every row in matrix do
      Calculate EBO for part #9
                                                       ▷ Our start value, needed to start recursion
 9: for Every part in order [8, 7, 6, 5, 4, 3, 2, 1] do
                                                                                      ▶ Recursion
      matrix = AllVals(Data)
11: end for
12: function ALLVALS(Data)
      for Every row in matrix (Every budget) do
                                                             ▶ Find optimal for every sub problem
13:
          OptimalData = FINDOPTIMAL(Data)
                                                                                  ▷ (every budget)
14:
15:
      end for
      return OptimalDataMatrix
16:
17: end function
18: function FINDOPTIMAL(Data)
                                         ▶ Find the setup with lowest EBO using previous optimal
19:
       while Money left do
          Array(i) = Part(i) + Matrix(budget-Part(i))

→ Matrix(idx) gives previous optimal

20:
      return min(Array)
                                                           ▷ Returning the array with lowest EBO
21:
22:
```

(5) The resultant efficient curve generated by the dynamic programming method can be seen in Figure 2, and the corresponding EBO values and strategies for some selected budgets are presented in Table 2.

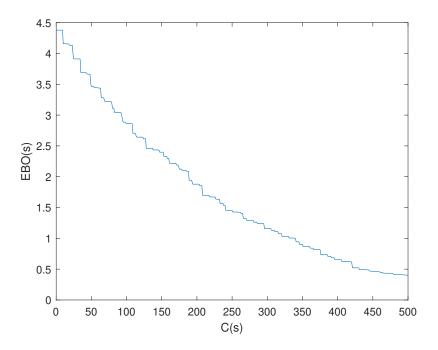


Figure 2: Lowest EBO for every budget

Table 2: Selected results from dynamic programming

| Budget | EBO | P1 | P2 | Р3 | P4 | P5 | P6 | P7 | P8 | P9 |
|--------|-------|----|----|----|----|----|----|----|----|----|
| 0 | 4.379 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 100 | 2.867 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 150 | 2.398 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 |
| 350 | 0.900 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 1 | 0 |
| 500 | 0.402 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 1 |

(6) Comparing the efficient curves obtained from the previous two methods, as seen in Figure 3, there is not substantial disparity. The results are somewhat different but it is clear that the few data-points the marginal allocation algorithm found are all common data-points with the dynamic programming algorithm. Note that at the far-right end of the graph the marginal allocation algorithm exceeds the budget. The reason is because the marginal allocation algorithm is breaking as soon as the budget is greater than the cost but not the other way around. The dynamic programming solution is breaking as soon as it hits the budget.

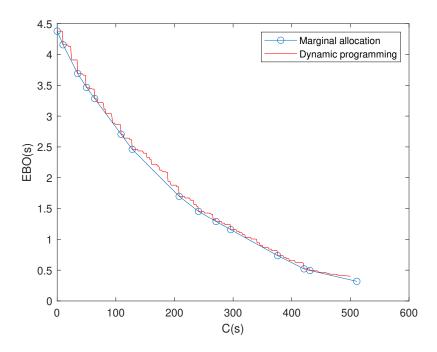


Figure 3: Dynamic programming and Marginal allocation solutions

Using the given budget, the marginal allocation algorithm's best solution which didn't exceed the budget was using 431 cost units. With this solution the EBO was 0.4946. If we would allow a solution a little over the given budget, the best solution would have been 511 with an EBO of 0.318.

Using the dynamic programming approach and 500 money, the best solution had an EBO of 0.402. This solution is under budget and better than the marginal allocation algorithms solution (not over budget). If we would have a little extra money we could have added 11 money to the budget and reduced the EBO with almost 25%.