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DSA 5113
Advanced Analytics & Metaheuristics
Group 24 - HW 5

Problem 1 – Simulated Annealing

Part a

To determine the initial temperature for this problem, the temperature values were increased until objective value is at least over 20,000.

Part b

The three different cooling schedules used for this problem are:

Cauchy schedule

$$t_k = \frac{T_0}{1 + k}$$

Boltzman schedule

$$t_k = \frac{T_0}{\log(1 + k)}$$

Alpha constant schedule

$$t_{k+1} = \alpha t_k$$

For number of iterations performed at a given temperature (M_k), a constant number, such as, 135 and 120 were used and also two different variations of greater iterations at lower temperatures were used. Both variations increase iterations when temperature drop to between 76%-90% of initial temperature, 51%-75% of initial temperature, 26%-50% of initial temperature, 6%-25% of initial temperature, down till it reaches 5% of initial temperature, which no iteration would be performed.

Part c

There are two different stopping criterion used for this problem. First method is when the specified total number of iterations (of the temperatures, k) has been reached. Second method is stopping when the cooling temperature reached 15% of the initial temperature.

So, using the maximum weight of **2,500** and **150** number selections, the results are in the table on the next page:

Algorithm	t_0	Cooling, t_k	M_k	# of temps	Iterations	# Items Selected	Weight	Objective
Simulated Annealing (k = 100, M_k = 30, 60, 105, 120, 135)	1000	$t_0/(1+k)$	variation-1	100	2,430	23	2,484.10	20,824.40
Simulated Annealing (k = 100, M_k = 30, 60, 105, 120, 135)	1000	$t_0/\log(1+k)$	variation-1	100	12,360	28	2,496.50	28,618.00
Simulated Annealing (k = 100, M_k = 30, 60, 105, 120, 135)	1000	$0.91t_{k-1}$	variation-1	100	3,735	30	2,481.20	28,701.20
Simulated Annealing (k = 100, M_k = 50, 100, 200, 400, 800)	1000	$t_0/(1+k)$	variation-2	100	13,650	27	2,498.60	29,451.10
Simulated Annealing (k = 100, M_k = 50, 100, 200, 400, 800)	1000	$t_0/\log(1+k)$	variation-2	100	376,550	30	2,488.40	31,962.90
Simulated Annealing (k = 100, M_k = 50, 100, 200, 400, 800)	1000	$0.91t_{k-1}$	variation-2	100	17,500	29	2,495.20	31,036.30
Simulated Annealing (k = 75)	800	$t_0/(1+k)$	135	75	10,125	23	2,490.90	21,378.60
Simulated Annealing (k = 75)	800	$t_0/\log(1+k)$	135	75	10,125	29	2,490.90	27,573.20
Simulated Annealing (k = 75)	800	$0.91t_{k-1}$	135	75	10,125	28	2,497.70	28,909.30
Simulated Annealing (stop at 15% of t_0)	750	$t_0/(1+k)$	120	6	720	23	2,492.70	22,344.50
Simulated Annealing (stop at 15% of t_0)	750	$t_0/\log(1+k)$	120	785	94,200	28	2,482.80	32,353.20
Simulated Annealing (stop at 15% of t_0)	750	$0.91t_{k-1}$	120	21	2,520	26	2,496.80	28,202.10

Problem 2 – Metaheuristics and Metaphors

Combination of random restarts, random walk, hill climbing with best improvement, and simulated annealing. The pseudocode:

```
1: input: starting solution,  $s_0$ 
2: input: neighborhood operator,  $N$ 
3: input: evaluation function,  $f$ 
4: input: initial temperature,  $t_0$ 
5: input: the cooling schedule,  $t_k$ 
6: input: the number of iterations for each temperature,  $M_k$ 
7: input: the number of iterations for random restart,  $R$ 
8: input: probability to use random walk-simulated annealing,  $p$ 
9: input: probability to use best improvement,  $1-p$ 
10:  $r \leftarrow 0$ 
11:  $current \leftarrow s_0$ 
12: while restart counter  $\leq R$  do
13:    $best\_neighbor \leftarrow current$ 
14:    $p\_current \leftarrow$  random probability between  $[0,1]$ 
15:   if  $p\_current < 1-p$ 
16:     for each  $s$  in  $N(current)$  do
17:       if  $f(s) < f(best\_neighbor)$  then
18:          $best\_neighbor \leftarrow s$ 
19:       end if
20:     end for
21:   else
22:     while stopping criterion not met do
23:        $m \leftarrow 0$ 
24:       while  $m < M_k$  do
25:          $s \leftarrow$  randomly selected solution from  $N(current)$ 
26:         if  $f(s) < f(best\_neighbor)$  then
27:            $best\_neighbor \leftarrow s$ 
28:            $current \leftarrow s$ 
29:         else
30:            $delta \leftarrow f(s) - f(current)$ 
31:            $epsilon \leftarrow$  a random number, uniformly drawn from  $[0,1]$ 
32:           if  $epsilon \leq e^{-delta/t_k}$  then
33:              $best\_neighbor \leftarrow s$ 
34:              $current \leftarrow s$ 
35:           end if
36:         end if
37:        $m \leftarrow m + 1$ 
38:     end while
39:   end while
40: end if
41: end while
```

Extra Credit:

- (i) Lunar Phases Metaheuristics
- (ii) Lunar Phases Metaheuristics is the phenomenon where time are important factors. The time determine the initial solution and what feasible solutions are “shown” according to the moon rotation. There are eight lunar phases to consider: New Moon, Waxing Crescent, First Quarter, Waxing Gibbous, Full Moon, Waning Gibbous, Third Quarter, and Waning Crescent. These different phases can either be robust and efficient or useless (end up showing only infeasible solutions). Other than the full moon phase, other phases with non-visible sides of the moon are consider tabu since the “invisible” side of the moon is full of unknown noises or unknown path. On the case of the New Moon phase, it helps show that a new initial solution is needed since that initial solution are most likely to be infeasible solution. Knowing these lunar phases (rotations of the moon) can help with fast forward to the right timing of the optimal solution. Although full moon would be the ideal phase and the one with 100% probability of the optimal solution, by using the other phase, the timing would be much more efficient than evaluating the full moon phase.

Problem 3 – More Extra-Credit (Tabu Search)

The tabu criterion is selection in the neighborhood that have less than 23 selections. Those values will be considered tabu-active for a period of time (called tabu tenure). The aspiration criterion to override this tabu search will be allowing those selections as long as they have feasible solutions.

Code files:

Group25_HW5_p1.py, Group25_HW5_tabuSearch.py.