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**IE 343 FINAL PROJECT**

**by**

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**IE 343 TERM PROJECT**

Knapsack is an NP-Hard problem where an optimal combination of items should be found under a capacity constraint. Each item has its own value and weight, the main purpose is to maximize the total value of selected items. However, the total weight of the chosen items cannot exceed the given capacity value. To solve this problem, the Simulated Annealing (SA) approach, which is a Meta-Heuristic method, is applied. SA tries to find better solutions by randomly modifying the current solution. This modification can increase or decrease the value of the objective function. Note that a higher objective function value is desired. Thus, the algorithm always accepts better solutions. However, worse solutions should also be accepted to get rid of the sub-optima problem (i.e., Hill Climbing). With probability, the algorithm should accept the worse solutions. With an iterative approach, the algorithm searches for better solutions until the stopping criteria are met. At the begging of the process, the probability of acceptance should be higher, and decrease over time. Algorithm 1 demonstrates the pseudo-code for the SA method.A screenshot of a computer program

Description automatically generated with low confidence

The algorithm has three hyper-parameters, which are maximum temperature, minimum temperature, and decay of temperature. A temperature variable starts from the given maximum temperature parameter, and it decreases depending on the decay of the temperature parameter. The algorithm lasts until the temperature reaches the minimum temperature value. The acceptance probability is determined based on both the current temperature value and the difference of objective values between current and neighbor solutions. Note that a higher temperature means a higher acceptance probability.

The parameters of the SA approach have an effect on the performance of the method in terms of computational time and objective value. Hence, these parameters must be tuned. For this reason, Table 1 indicates the effect of the maximum temperature parameter, Table 2 shows the effect of decay of the temperature parameter, and Table 3 displays the effect of the minimum temperature parameter.

|  |  |  |
| --- | --- | --- |
| Maximum Temperature | Objective Value | Elapsed Time (ms) |
| 100 | 1460 | 39 |
| 200 | 1536 | 40 |
| 300 | 1564 | 43 |

Table 1. Effect of Maximum Temperature Parameter

|  |  |  |
| --- | --- | --- |
| Decay of Temperature | Objective Value | Elapsed Time (ms) |
| 0.99 | 1620 | 43 |
| 0.95 | 1466 | 27 |
| 0.90 | 1349 | 13 |

Table 2. Effect of Decay of Temperature Parameter

|  |  |  |
| --- | --- | --- |
| Minimum Temperature | Objective Value | Elapsed Time (ms) |
| 5 | 1530 | 40 |
| 10 | 1451 | 27 |
| 15 | 1416 | 15 |

Table 3. Effect of Minimum Temperature Parameter

To obtain the results above, the other parameters are kept the same: Maximum Parameter: 200, Decay of Temperature: 0.95, Minimum Temperature: 10. Besides, each result is an average of three-run to reduce the impact of random seed.

According to the results, a higher maximum temperature parameter increases both the objective value and computational time. A higher decay of temperature also increases both the objective value and elapsed time. A lower minimum temperature value increases both the objective value and the required time. As a result, the decay temperature as 0.99, maximum temperature as 200, and minimum temperature as 10 are decided to get a balanced performance between the objective function and the computational time. Since, a higher decay of temperature gains more objective than the other parameters. Therefore, the decay of temperature is kept as the highest while the other parameters are determined as the medium value.