

Generic Algorithm Implementation of Approximation Algorithm using Simulated Annealing (SA)

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ABSTRACT

This paper describes a complementary mechanism that attempts to learn the structure of the search space over multiple runs of SA on a given problem[29] (Best fit Problem & First Fit Decreasing). Specifically, we introduce a mechanism that attempts to predict how (UN) promising a SA runs is likely to be, based on probability distributions that are "learned" over multiple runs. The distributions, which are built at different checkpoints, each corresponding to a different value of the temperature ('temperature' is a variable which decrements its value at each step-as SA has a great relation with physics, the variable is termed in this manner) parameter used in the procedure, approximate the cost reductions that one can expect if the SA run is continued below these temperatures.

Simulated annealing is a method of finding optimal values numerically. It chooses a new point, and (for optimization) all uphill points are accepted while some downhill points are accepted depending on probabilistic criteria. For certain problems, simulated annealing may be more efficient than exhaustive enumeration — provided that the goal is to find an acceptably good solution in a fixed amount of time, rather than the best possible solution.

Keyword

One bin packing, multiple bins packing, simulated annealing, best fit problem, first fit decreasing, meta- heuristics, constraints (parameters).

1. INTRODUCTION

Simulated Annealing is a local search method based on local optimization. In this method each trial solution in the solution space has a cost, and the objective is to find a feasible solution of least cost. The method is iterative. In each cycle we try to move from the current trial solution S to a neighboring point S' in the solution space in an effort to find a better trial solution.

Let us assume that the problem is a minimization problem. If $\text{cost}(S') < \text{cost}(S)$, S' becomes the new trial solution; the move from S to S' is then called a downhill move. If $\text{cost}(S') > \text{cost}(S)$, S' becomes the new trial solution with probability $p = \exp(-\Delta/\text{temp})$, where temp is a parameter known as the temperature and $\Delta = \text{cost}(S') - \text{cost}(S)$; S is retained as the trial solution with probability $(1-p)$. Thus S' can become the new trial solution even when its cost is higher than the cost of the current trial solution S ; this kind of move from S to S' is called an uphill move. This deliberate choice of an inferior trial solution with a non-zero probability helps to ensure that the procedure does not get trapped in a local minimum. By slowly reducing the temperature, the probability p is reduced in the course of the iteration as better trial solutions are found.

Bin packing [1] problem solves the packing of objects of different volumes into a finite number of bins of capacity V in a way that minimizes the number of bins used. The approximation algorithm is applied on Multiple Bin Packing Problem in such a way that the algorithm produces the minimum number of bin used as a result.

2. LITERATURE REVIEW

2.1. Bin Packing Problem

The bin packing problem asks for the minimum number of identical bins of capacity C needed to store a finite collection of weights $w_1, w_2, w_3, \dots, w_n$ so that no bin has weights stored in it whose sum exceeds the bin's capacity. Traditionally the capacity C is chosen to be 1 and the weights are real numbers which lie between 0 and 1, but here, for convenience of exposition, I will consider the situation where C is a positive integer and the weights are positive integers which are less than the capacity.

2.2. Simulated Annealing

Simulated Annealing (SA) is a general-purpose search procedure that generalizes iterative improvement approaches to combinatorial optimization by sometimes accepting transitions to lower quality solutions to avoid getting trapped in local minima. SA procedures have been successfully applied to a variety of combinatorial optimization problems, including Traveling Salesman Problems, Graph Partitioning Problems, Graph Coloring Problems[20], Vehicle Routing Problems[15], Design of Integrated Circuits, Minimum Make-span Scheduling Problems as well as other complex scheduling problems, often producing near-optimal solutions, though at the expense of intensive computational efforts. The procedures, typically requiring that the procedure be rerun (iterate) a large number of times before a near optimal solution are found. Other names of Simulated Annealing are Monte Carlo Annealing[5], Statistical Cooling[6], Probabilistic Hill Climbing[7], Stochastic Relaxation[9], Probabilistic Exchange Algorithm[8] etc.

2.3. Problem Definition

The problem is categorized into two phases i.e., Phase I & Phase II

2.3.1. Phase I: The goal is to fit the different weighted objects into a single bin with the least cost function.

2.3.2. Phase II: The goal is to fit the different weighted objects into multiple bins such that minimum number of bins used.

2.4. Proposed Work

2.4.1. Proposed Algorithm For Simulated Annealing:

Procedure SA

```
{
    input a trial solution S; c = cost(S); c* =
infinity; freezecount = 0; initialize temp;
    initializefrzlim, sizefactor, tempfactor,
minpercent, tcent;
    while ( freezecount<frzlim )
    {
        changes = trials = 0;
        while ( trials <sizefactor * N )
        {
            /* N is determined by the size of the
problem */
            trials = trials + 1;
            generate a random neighbour S' of S;
            c' = cost(S');  $\Delta = c' - c$ ;
            if (S' is feasible and
cost(S') < c* )
            {
                S* = S'; c* = cost(S');
            }
            /* save best feasible
solution found so far */
            if ( $\Delta < 0$ )
            {
                changes =
changes + 1; c = c'; S = S';
            } /* downhill move */
            else
            {
                /* possible uphill move */
                choose a
random number r in [0,1];
                if ( r <=
exp(- $\Delta$ /temp) )
                {
                    changes = changes+1; c = c'; S = S';
                }
            }
            if ( changes/trials >tcent ) temp
= 0.5 * temp; /* reduce temperature quickly */
            else temp = tempfactor * temp;
            /* reduce temperature slowly */
            if
( changes/trials <minpercent ) freezecount =
freezecount+1;
            elsefreezecount = 0;
        }
        output the final solution S*; /* S* is a
feasible solution of minimum cost */
    }
}
```

2.5. Setting up SINGLE BIN PACKING PARAMETERS and Approximation Analysis with SIMULATED ANNEALING

We need to initialize parameters based on ITEMLIST (total number of items) and MAXBINSIZE

Round_1 : ITEMLIST =5; MAXBINSIZE = 100;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 50%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

Round_2 : ITEMLIST =15; MAXBINSIZE = 300;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 25%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

Round_3 : ITEMLIST =75; MAXBINSIZE = 900;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 15%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

Round_4 : ITEMLIST =225; MAXBINSIZE = 2700;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 15%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

Round_5 : ITEMLIST =675; MAXBINSIZE = 8100;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 10%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

Round_6 : ITEMLIST =2025; MAXBINSIZE = 24300;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 10%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

Round_7 : ITEMLIST =6075; MAXBINSIZE = 72900;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 10%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

Round_8 : ITEMLIST =18225; MAXBINSIZE = 218700;
 INITIALSOLUTIONLIST (no. of objects to create
 an initial_Soln) = ITEMLIST * 60%
 REDUCEDBINSIZE = MAXBINSIZE * 10%;
 NEIGHBOURCREATION=INITIALSOLUTIONLIST * 33%

2.6. Setting up Multiple BIN PACKING PARAMETERS and Approximation Analysis with SIMULATED ANNEALING

We need to initialize parameters based on MAXBINSIZE and MAXOBJNO

Round_1 : MAXOBJNO=6; MAXBINSIZE =10;[where $x=6$; $y=10$ with $6 : 10 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (3 objects at a time)

Option 3 -> Replace 25 % (1 or 2 objects at a time based on floor or ceil values);

Round_2 : MAXOBJNO=12; MAXBINSIZE =20;[where $2x=12$; $2y=20$ with $12 : 20 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (6 objects at a time)

Option 3 -> Replace 25 % (3 objects at a time);

Round_3: MAXOBJNO=24; MAXBINSIZE =40;[where $2x=24$; $2y=40$ with $24 : 40 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (12 objects at a time)

Option 3 -> Replace 25 % (6 objects at a time);

Round_4 : MAXOBJNO=48; MAXBINSIZE =80;[where $2x=48$; $2y=80$ with $48 : 80 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (24 objects at a time)

Option 3 -> Replace 25 % (12 objects at a time);

Round_5 : MAXOBJNO=96; MAXBINSIZE =160;[where $2x=96$; $2y=160$ with $96 : 160 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (48 objects at a time)

Option 3 -> Replace 25 % (24 objects at a time);

Round_6 : MAXOBJNO=192; MAXBINSIZE =320;[where $2x=192$; $2y=320$ with $192 : 320 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (96 objects at a time)

Option 3 -> Replace 25 % (48 objects at a time);

Round_7 : MAXOBJNO=384; MAXBINSIZE =640;[where $2x=384$; $2y=640$ with $384 : 640 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (192 objects at a time)

Option 3 -> Replace 25 % (96 objects at a time);

Round_8 : MAXOBJNO=768; MAXBINSIZE =1280;[where $2x=768$; $2y=1280$ with $768 : 1280 = 3 : 5$ ratio]

For NEIGHBOURCREATION: Option 1 -> Replace All randomly generated objects

Option 2 -> Replace 50% (384 objects at a time)

Option 3 -> Replace 25 % (192 objects at a time);

3. RESULT ANALYSIS

3.1. For One Bin packing

Targ et (T): To reac h Max Bin Size	Round 1: Trails =25	Round 2: Trails = 50	Round 3: Trails = 100	Round 4: Trails = 200	Round 5: Trails = 400	Round 6: Trails = 800	Round 7: Trails = 1600	Round 8: Trails = 3200	Round 9: Trails = 6400	Average Bin Size Reached (T)	Differential Error: Abso lute Value of (T`-T)/T
	Frzlim =5; trail Limit=5	Frzlim= 10; trail Limit=5	Frzlim= 20; trail Limit=5	Frzlim= 40; trail Limit=5	Frzlim= 80; trail Limit=5	Frzli m= 160; trail Limit =5	Frzli m= 320; trail Limit =5	Frzli m= 640; trail Limit =5	Frzli m= 1200; trail Limit =5		
100	95	99	82	100	72	98	100	91	99	93	0.07
300	300	300	300	299	300	300	300	300	300	300	0
900	844	897	899	900	884	900	900	900	900	896	0.004444
2700	2684	2696	2576	2698	2694	2696	2699	2700	2700	2683	0.006296
8100	7927	8063	8024	8097	8093	8100	8100	8099	8100	8067	0.004074
24300	24012	24154	24219	24187	24199	24230	24259	24279	24178	24191	0.004485
72900	70912	71861	72454	72865	72756	72888	72565	72701	72876	72431	0.006433
218700	217772	216438	215792	216754	214778	217865	21720	216820	213820	21637	0.010640

3.1. Analysis of Approximation Algorithms of Different Rounds:

FIRST-FIT Algorithm				Analysis of Approximation Algorithms					
Trials	MaxBin Size	Max Object Number	Minimum Number of Bin Required(OPT)	BFD/FFD::Bound is :: $11/9 \text{ OPT} + 1$ bins	Speciality Case :: FFD bound is tight :: $11/9 \text{ OPT} + 6/9$ bins	Modified Bin Packing (MFFD) :: $71/60 \text{ OPT} + 1$ bins	Bound 1 :: MFFD is bounded by 1.18 OPT	Bound2 :: 1.22 OPT for FFD	Tight Upper Bound for FF :: $17/10 \text{ OPT}$ bins (Recent 2013)
Round 1	10	6	4	5.888889	5.55555555	5.7333333	4.72	4.888	6.8
Round 2	20	12	6	8.333332	7.99999999	8.0999998	7.08	7.32	10.2
Round 3	40	24	12	15.66664	15.3333333	15.199996	14.16	14.64	20.4
Round 4	80	48	24	30.33338	29.9999994	29.399992	28.32	29.28	40.8
Round 5	160	96	48	59.66666	59.3333322	57.799998	56.64	58.56	81.6
Round 6	320	192	96	118.3331	117.999997	114.59999	113.28	117.12	163.2
Round 7	640	384	192	235.6662	235.33329	228.19993	226.56	234.24	326.4
Round 8	1280	768	384	470.3332	469.999984	455.39999	453.12	468.48	652.8

Table3: Work in Jan 2013 [27]

3.2.For Multiple Bin packing:

Table 1: Resultant Data

Trials	Max Bin Size	Max Object Number	Minimum number of Bin Required (OPT)
Round 1	14	4	3
Round 2	28	8	4
Round 3	56	16	8
Round 4	112	32	16
Round 5	224	64	32
Round 6	448	128	64
Round 7	896	256	128
Round 8	1792	512	256

Trials	Max Bin Size	Max Object Number	Minimum number of Bin Required (OPT)
Round 1	14	4	5.1
Round 2	28	8	6.8
Round 3	56	16	13.6
Round 4	112	32	27.2
Round 5	224	64	54.4
Round 6	448	128	108.8
Round 7	896	256	217.6
Round 8	1792	512	435.2

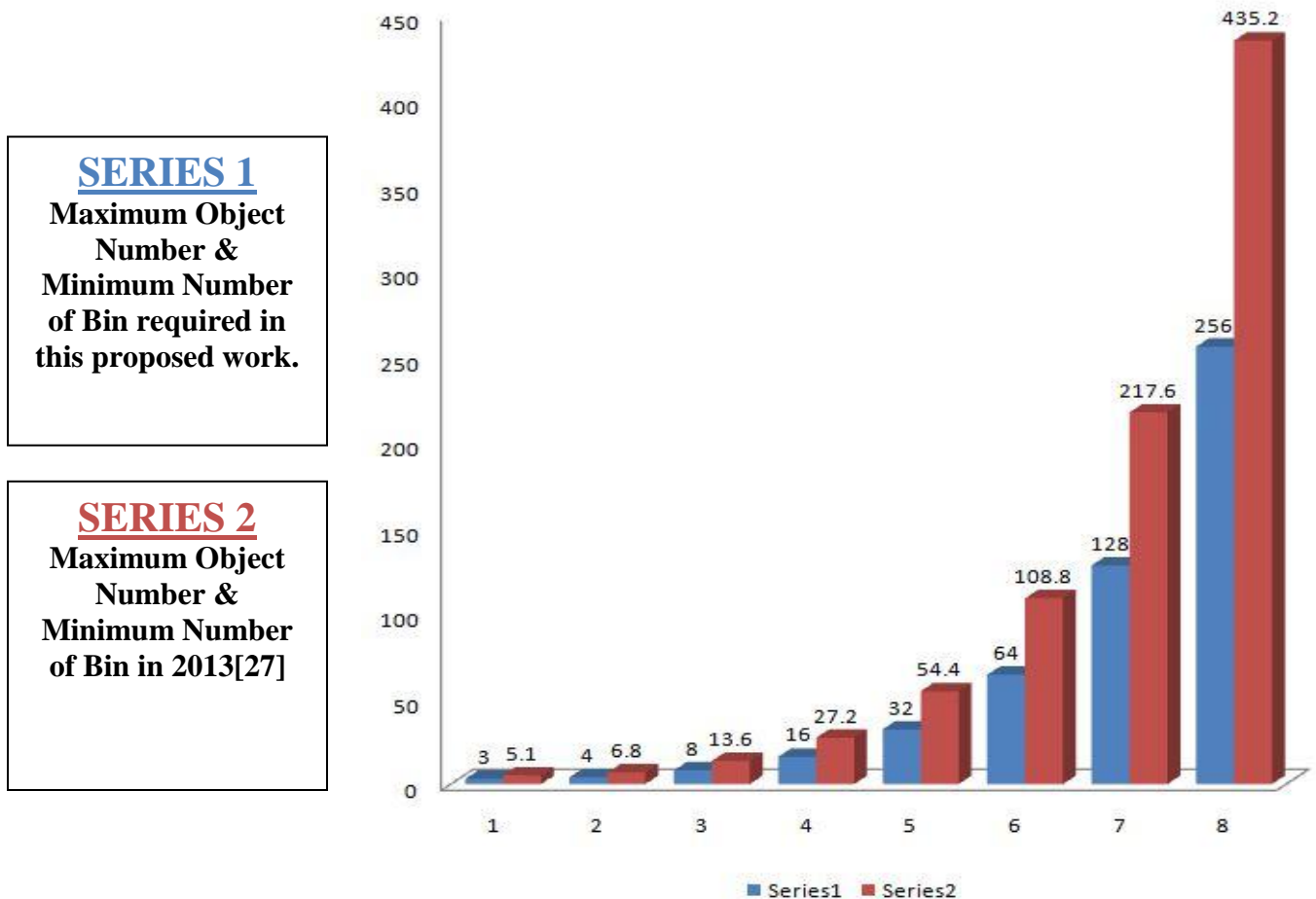


Figure 1: Comparison plot of Resultant data.

Table 3: Resultant Data

Trials	Max Bin Size	Max Object Number	Minimum number of Bin Required (OPT)
Round 1	4	14	7
Round 2	8	28	15
Round 3	16	56	28
Round 4	32	112	56
Round 5	64	224	112
Round 6	128	448	224
Round 7	256	896	448
Round 8	512	1792	896

Trials	Max Bin Size	Max Object Number	Minimum number of Bin Required (OPT)
Round 1	4	14	11.9
Round 2	8	28	25.5
Round 3	16	56	47.6
Round 4	32	112	95.2
Round 5	64	224	190.4
Round 6	128	448	380.8
Round 7	256	896	761.6
Round 8	512	1792	1523.2

SERIES 1

Maximum Object Number & Minimum Number of Bin required in this proposed work.

SERIES 2

Maximum Object Number & Minimum Number of Bin in 2013[27]

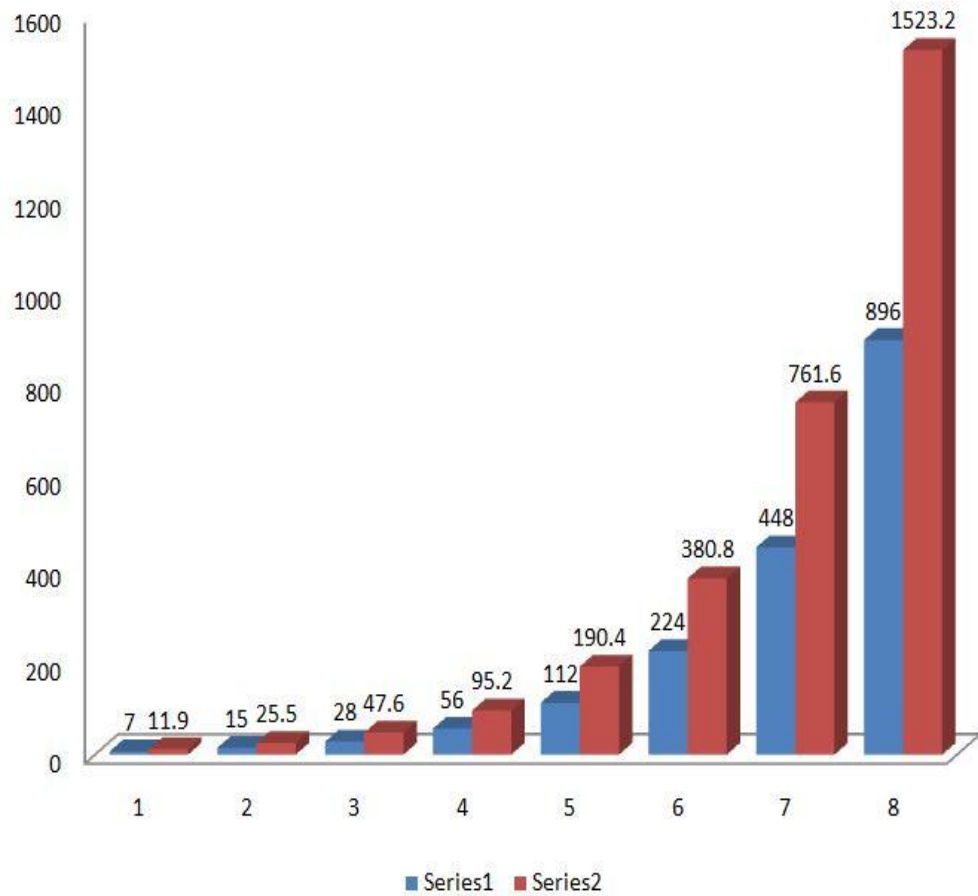


Figure 2: Comparison plot of Resultant data in a Reversed Ratio.

4. CONCLUSIONS

This work has been accomplished on a single bin of variable sizes with the implementation of simulated annealing on that particular bin with least runtime complexity. Also on multiple bins of variable sizes with the implementation of simulated annealing with minimum number of bins used, got accomplished on this work. A future aspect is to implement the above problems of 1bin packing as well as multiple bins packing in a 2-dimensional pattern.

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