Enhanced Approach on Permissible Data Sets Using Swarm and Genetic Intelligence

V Prasad, G N V Raja Reddy

ABSTRACT--- This work focuses on the artificial way of analysing large datasets using genetic and evolutionary algorithms with multiple features i.e., algorithms are embedded with bin packing problems which generates Hybrid particle swarm optimization (HPSO), Multi spatial genetic algorithm (MSGA) which are further applied on a cancer dataset for classification of bins in the datasets. Random population generated by these algorithms, the fitness values, evaluation procedure plays a vital role. The algorithms increase the count of features and prune for obtaining the optimistic values with random machine learning protocols and the comparative analysis as shown in the graphs and tables. The results are analysed and compared to obtain the most suitable and efficient algorithm for the permissible dataset.

Keywords: Evolutionary Computing, Natural Computing, Hybrid Swarm, Multi Spatial & Comparative Analysis

I. INTRODUCTION

One Dimensional Bin Packing Problem (ODBPP)

ODBPP can be stated as follows: Set of n objects each with a given weight $w_i > 0$. Bins of a given capacity C ($C > w_i$) so that bins number could be minimized. ODBPP is used using several optimization techniques but the process linking of ODBPP with genetic may produce good resultant ***[1]*** as discussed in ***Section 2*** and the searching process also becomes easy ***[2]*** the application of Genetic Algorithm (GA) and Particle Swarm Optimization adds an extra composite factor for the resultant trace ***[3].*** Better solutions can be obtained by generating the chromos by the GA and these chromos are useful in

identifying the problems likely time tabling, packing problems and vehicle encounter problems by applying the same in GA operators.

The particles in the swarm are mainly depended on the velocity and the position vectors with which it should transfer. The items are maximized or minimized based on the flexibility of the chromos overlap.

The highpoints are mentioned in the ***Section 2***, likely algorithms are clarified in ***Sections 3 and 4***. In ***Section 5***, the ODBPP is solved and the outcomes are displayed in ***Section 6***. Finally, concluded in ***Section 7***.

II. ROLE OF ODBPP WITH OPTIMIZATION ALGORITHMS

Implementation of bin packing problem ***[4]*** was done using the best first decreasing algorithm. The ODBPP approach begins with a left fill bottom approach considering he bins(n) and its capacity (L) for each and every individual unit (i). The concept of packing all the objects and minimizing the bins makes this work more popular and reusable at extent levels.

The target is made for the quality solutions which are evolved from the packing plan using the ODBPP concept, which makes the computer-assisted approaches to easily handle the input series in any type or any format ***[5].*** The critical solutions to the problems can be handled by the other visions of BPP i.e., 2DBPP, 3DPP and so on considered to be multi-dimensional bin packing problem (MDBPP) ***[6]*** based on the algorithm procedures of DFS mentioned with the best fit likely (next-fit, auto-fit, general-fit, bottom-left -fit, bottom-right -it and so on).

Hybrid ***[6]*** procedure for ODBPP is implemented using features with the use of lower bounding, referential initial solution to the dual min-max problem, load redistribution, differencing and other balancing and unbalancing resource sharing from the impute string.

The mentioned literature acts as the benchmark in obtaining the optimal solution. Emphasis Algorithms ***[7],*** and 2DBPP genetic algorithms are further used for resolving the issue of minimum objects at a complexity of O(N3) ***[8]***. Here, also the same implementation of bottom-left is fixed and best fit for obtaining the optimal solution ***[9]***.

2.1 GENETIC ALGORITHM IN MULTI OBJECTIVE BPP

The process of natural selections for natural genetic chromo identification is provided by GA ***[10]*** both theoretically and empirically to provide solutions for multi objects bin packing

2.1.1 FITNESS

The fitness of MDBPP is obtained as the sum of profit-oriented chromosomes and less bins ***[11]***

Fitness Function(F) =P1/P2

Where,

P1= Total sum of profit & P2=Total Bins

The probability $Ps(i)$ ***[12].*** obtained to be calculated by the selection operator, as

$$Ps(i) = \frac{f(i)}{\sum_{j=1}^{N} f(j)}$$

Where Ps (i) and f(i) are the probability of selecting the fitness value for the i^{th} chromosome respectively followed with the single- and two-point crossover among multi and

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uniform point crossover ***[13].*** *The embedded bin packing problem in GA produces AGA.*

Later, the probability of mutation is given in a flipped order either 0 or 1for the input string which is entered. The input string is pruned in either flip or interactive or random mode as mentioned in ***[14]*** to obtain the global maxima and restrictive derivatives at each iteration and their respective levels.

.2.2 ROLE OF PARTICAL SWARM OPTIMIZATION

Heuristic search could be used as a process but while Considering particle swarm optimization (PSO) as a computational method to measure the quality gives the accurate and prominent resultants. It solves a problem by search-space. The best-known positions are obtained by the dubbed or the duplicate particles in the input to straight forward the algorithm ***[15]*** in resulting the tuned data as the output, the detailed information displayed in the implementation Section 3**.**

The process of reducing the bins of the object is only possible by reducing the volume (V) by seducing completely it to position as volume (V/2). The arrival of the volume V as V/2 automatically reduces the bins which leads to the optimal solution. *The embedded bin packing problem in PSO produces HPSO.*

III. IMPLEMENTATION METHOD

The object classification of the individual at every iteration is classified as bins likely to be large, medium, small and tiny. The segregation is done as per the bins and the noticed objects and the resolution data input in it.

3.1 FUNCTIONING OF THE DEVELOPED SYSTEM

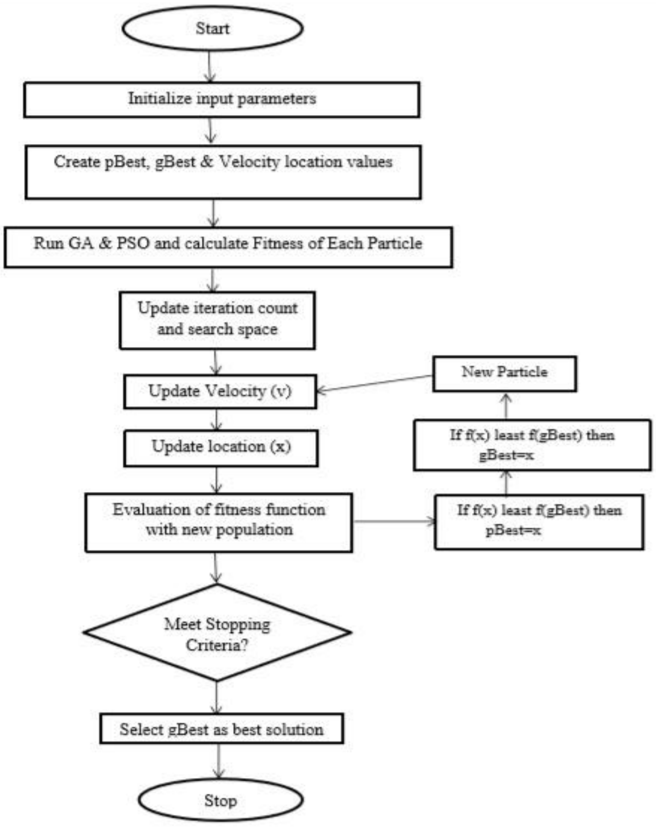

Fig 1: **The figure represents the flow of optimization algorithms with the Concept involved using BPP. It shows the iterations based on the velocity and the process in identifying the Pbest and Gbest values. Finally, the process ends with finding the global positioning value which is more feasible for a solution to be attained.**

3.2 METHODOLOGY

Step 1: Bin allocation to be finalized at initial stage

Step 2: Bins to be filled or filed as per the largest bin rule and proceed to the next bin based on the completion or concurrence availability of the existing bin

Step 3: Choose the best fit algorithms as needed and move for the next level of search to trace the particles or chromes from large level to tiny level

Step 4: Repeat the process to all the bins as mentioned in the steps 1 to 3

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Step 5: Pack the remaining items to new bins, once the data is found accurate

Scan, each bin to prune the new item obtained and pack the same using the nearing bin ***[16].***

3.3 Algorithm Implementation

x_k^i	-	position
v_k^i	-	velocity
p_k^i	-	latest particle position
p_k^g	-	latest swarm position
C_1, C_2	-	Cerebral parameters
r_1, r_2	-	Temp Variables 0 and 1

\

Updated Particles and bin positions:

$$x_{k+1}^i = x_k^i + v_{k+1}^i$$

$$v_{k+1}^i = v_k^i + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (p_k^g - x_k^i) \quad [10]$$

Step #1: Initialize and set the constraints at the level of iteration as $k_{\max}$, C_1, C_2, which initiates the particle positions as x_0^i € D in IR^n for i = 1, …., p and sets the k value of the random variable to 1.

Step #2: Optimize and evaluate f_k^i with space coordinates x_k^i usinf

If $f_k^i \le f_{best}^i$ where $f_{best}^i = f_k^i, p_k^i = x_k^i$.

If $f_k^i \le f_{best}^g$ where $f_{best}^g = f_k^i, p_k^g = x_k^i$, keep updating all the particle velocities and positions based on the incremented k value and repat the steps 1 and 2 continuously until k reach its saturation point

Step #3: Terminate

3.3 PROPOSED SYSTEM

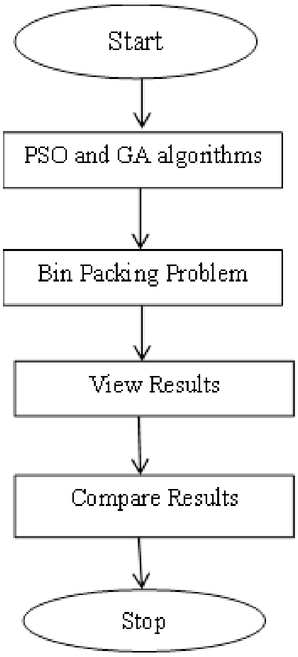


Fig 2: **The figure representing the entire flow of the proposed model**

IV. RESULTANT OUTCOMES

The results are analysed individually and compared to obtain the most suitable and efficient algorithm.

4.1 Input given to the Algorithms

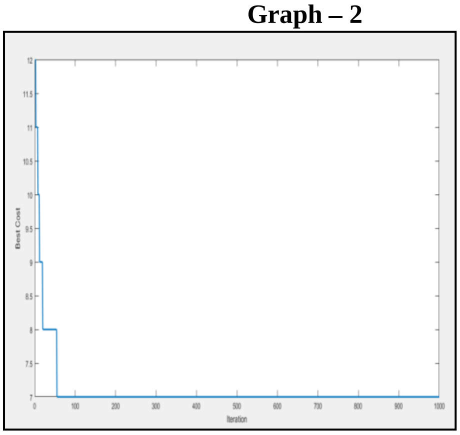
These are the data values given and the output generated when the BPP is applied to the PSO and GA algorithms using

 # CASE 1 # FOR CASE – 1000 (HPSO & AGA)

Table -2

Iteration Number (1 - 1000)	Best Cost (AGA)
1&2	12
3 - 7	11
8 - 11	10
12 - 19	9
20 - 54	8
55 - 1000	7

Graph – 2



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 # CASE 2 # FOR CASE – 800

Table -3

Iteration Number (1 - 800)	Best Cost (HPSO)
1 - 6	11.3636
7 - 10	11.1818
11 - 18	11
19 - 22	9.6667
23 - 39	9
40&41	8.25
42 - 197	8
198 - 206	7.2857
207 - 800	7

Graph-3

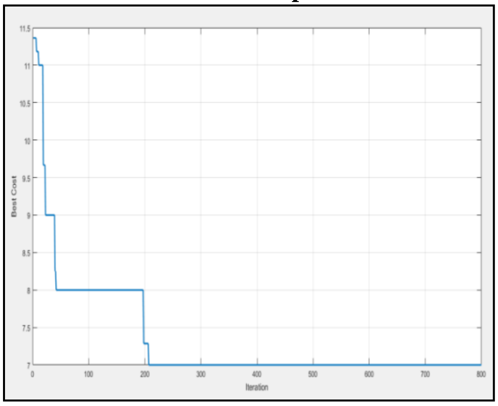
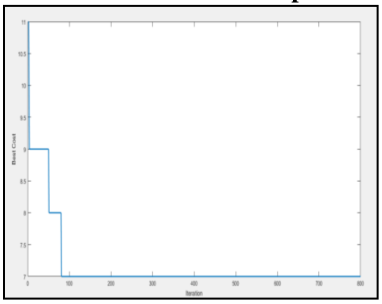


Table -4

Iteration Number (1 - 800)	Best Cost (AGA)
1&2	11
3	10
4 - 50	9
51 - 80	8
81 - 800	7

Graph-4



 # CASE 3 # FOR CASE – 600

Table -5

Iteration Number (1 - 600)	Best Cost (HPSO)
1 - 4	10
5 - 42	9
43 - 213	8
214 - 600	7

Graph-5

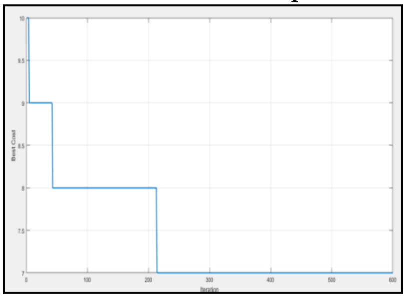
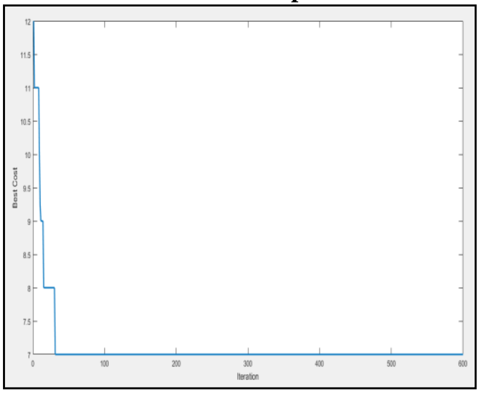


Table -6

Iteration Number (1 - 600)	Best Cost (AGA)
1	12
2 - 8	11
9	10
10	9.25
11 - 14	9
15 - 30	8
31 - 600	7

Graph-6



 # CASE 4 # FOR CASE – 400

Table – 7

Iteration Number (1 - 400)	Best Cost (HPSO)
1 – 5	11
6 – 10	10
11 – 23	9
24 – 120	8
121&122	7.5714
123 – 400	7

Graph- 7

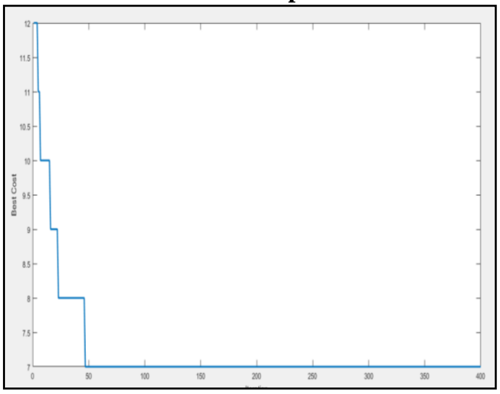
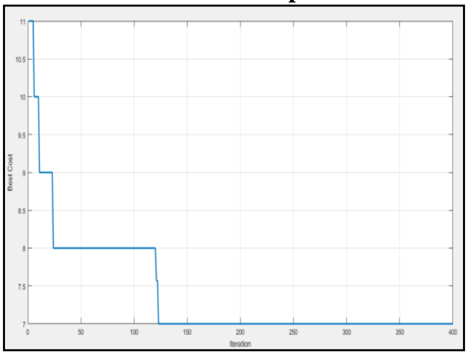


Table – 8

Iteration Number (1 - 400)	Best Cost (AGA)
1 - 4	12
5&6	11
7 - 15	10
16 - 22	9
23 - 46	8
47 - 400	7

Graph- 8



 # CASE 5 # FOR CASE – 200

Table – 9

Iteration Number (1 - 200)	Best Cost (HPSO)
1	11.5455
2&3	11.3636
4 - 8	10.4
9 - 11	10
12 - 26	9
27 - 200	8

Graph - 9

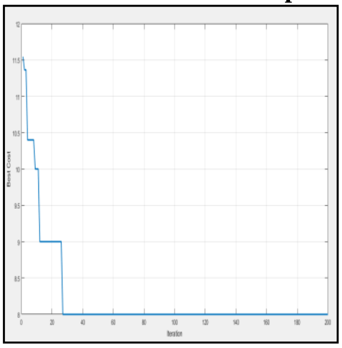
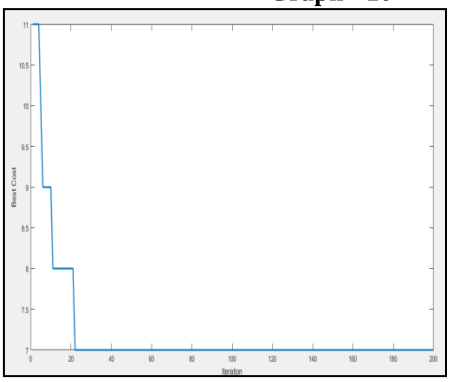


Table – 10

Iteration Number (1 - 200)	Best Cost (AGA)
1 - 4	11
5	10
6 - 10	9
11 - 21	8
22 - 200	7

Graph - 10



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ANALYSIS OF RESULTS

Table – 11

Iteration No.	Best cost HPSO	Best cost AGA
1&2	12	12
3	11.2	11
4-8	11	11
9-15	10.2	10
16-20	9.22	9
21-41	9	8
42-176	8	7

Graph -11

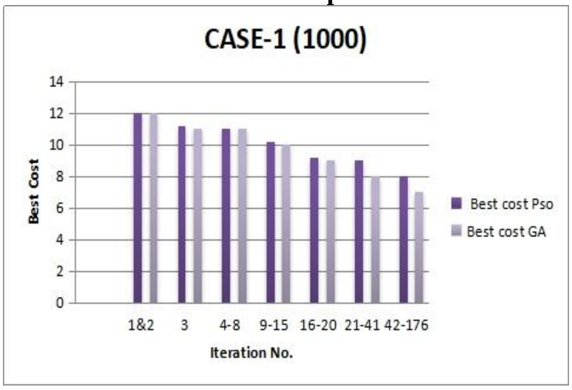


Table – 12

Iteration No.	Best cost HPSO	Best cost AGA
1-6	11.3636	9
7-10	11.1818	9
11-18	11	9
19-22	9.6667	9
23-39	9	9
40&41	8.25	9
42-197	8	7

Graph -12

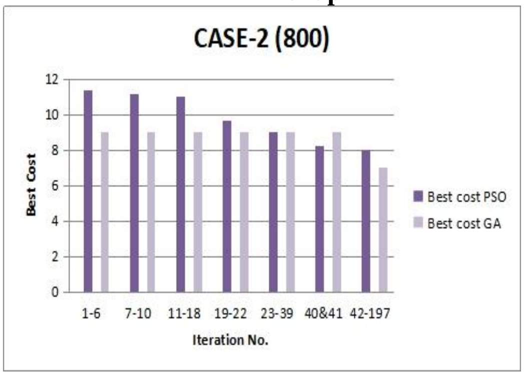


Table – 13

Iteration No.	Best cost HPSO	Best cost AGA
1-4	10	11
5-42	9	8
43-213	8	7

Graph -13

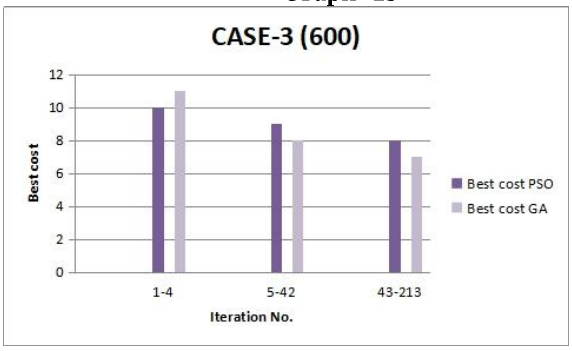


Table – 14

Iteration No.	Best cost HPSO	Best cost AGA
1-5	11	12
6-10	10	10
11-23	9	9
24-120	8	7

Graph -14

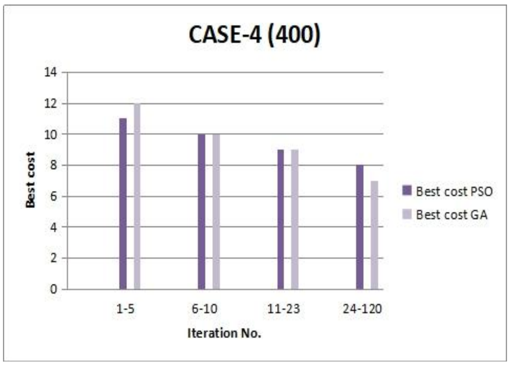
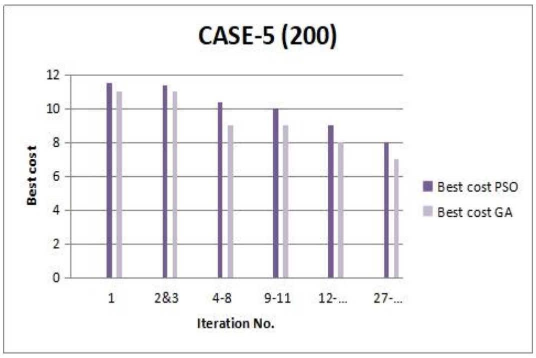


Table – 15

Iteration No.	Best cost HPSO	Best cost AGA
1	11.5455	11
2&3	11.3636	11
4-8	10.4	9
9-11	10	9
12-26	9	8
27-200	8	7

Graph -15



V. CONCLUSION

The project as mentioned is implemented on the biological population of cancer datasets. The new populations are arrived using both the GA and PSO in combination with ODBPP and MDBPP. The key difference is in the mechanism to produce a new population of solutions using the solutions from the old population. The objective of this project is to apply BPP for both PSO and GA. The analysis is carried out in five cases. The observations and recordings as shown in Section 4, the GA comparatively with PSO is leading a good scope with embedded ODBPP and MDBPP in it.

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