Original Article

Analysing Quantitative Assigment Problem with different Metaheuristic Algorithm

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Abstract

The attraction towards the Swarm Intelligence (SI) is increasing day by day in the various research fields. There are many swarm-based optimizations are being introduced since early 60's, Evolutionary Algorithms (EA) are the most updated one, Grey Wolf Optimization Algorithm. All Evolutionary Algorithms have proving their capability to resolve most of the optimization problems. These algorithms are using for training the neural networks in this paper. The main difficulty for any optimization problems is selecting the correct values of parameters to get feasible results. The main idea to get best convergence rate and best performance is to vary the parameters of the algorithms. Quadratic Task Issue (QAP) is a NPhard combinatorial advancement issue, in this manner, settling the QAP requires applying at least one of the meta-heuristic calculations. This paper presents a similar report between Meta-heuristic calculations: Comparing the optimization algorithms, Particle Swarm Optimization (PSO), Multi Verse Optimization (MVO) and Grey Wolf Optimization (GWO) before and after tuning the parameters with three different datasets.

Keywords: EA, PSO, MVO, GWO, Parameters, Datasets, Neural Networks.

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INTRODUCTION

As of late, a few quantities of nature motivated improvement methods have been created. These incorporate Particle Swarm Optimisation (PSO), Gravitational search algorithm (GSA), Hereditary Calculation (GA), evolunitory algorithm (EA),,Multiverse optimization algorithm(MOA), The shared objective of these calculations is to track down the best nature of arrangements and better assembly execution. To do this, a nature propelled variation ought to be furnished with investigation and abuse to guarantee seeing as worldwide ideal. According to Eiben and Schippers [1], double-dealing and investigation in nature enlivened figuring are not reasonable because of absence of a typically acknowledged assessment and on the opposite side, with expansion in one capacity, the other will debilitate as well as the other way around. In order to solve real time problem we need to analyse and examine the variants which can solve real life problem, these optimization are used to perform population based variant [2].One of the most commonly used Evolutionary variant is Particle Swarm Optimization is capable of optimum, convergence speed, and simplicity.

Meta-heuristic algorithm are issue free algorithmic structures that give a bunch of rules or systems to look through close ideal arrangements. Most meta-heuristic calculations are propelled by the cycles of nature natural advancement or potentially the social way of behaving of species. To imitate the learning, variation, and advancement conduct of species, different meta-heuristic calculations have been created. A portion of these calculations center around changing and further developing a solitary competitor arrangement, like reenacted tempering, unthinkable hunt, and iterated neighborhood search. While others are populace based, i.e., different applicant arrangements are kept up with and improved during the inquiry. In this examination, four populace based meta-heuristic algorithms: Particle swarm optimization (PSO), Multiverse optimization algorithm (MOA), grey wolf optimization algorithm.

Most upgrade issues can be tended to by using any extraordinary computation. Conceivably the principal class of transformative clas is (GA). The possibility of GA was introduced by John Holland in 1970s at School of Michigan [1].Genetic computation are requested as overall chase heuristics that uses iterative cycle to get needed plans. GA for the most part gives derived deals with serious consequences regarding the various issues. GA uses different regular techniques like inheritance, assurance, cross breed or recombination, change and increase. Since GA can manage both discrete and constant elements, it will in general be used to handle complex improvement problems.GA has been extraordinarily viable in various issues, for instance, upgrade, plan and booking [7], power systems [8],data dealing with, etc.

The progression issues can in like manner be easily settled by an imaginative circled perspective known as Large number Information (SI). The possibility of SI was introduced by Gerardo Beni and Jing Wang in 1989, who at first got pushed from the normal models, for instance, bird hurrying, underground bug territories, animal gathering, fish mentoring and bacterial turn of events. An undertaking was made to arrangement various estimations or appropriated decisive reasoning contraptions considering the regular eccentricities or systems. (PSO) was made by Kenned during the 1990s [2]

The chief idea in PSO is that each particle tends to a potential game plan which it revives according to two critical kinds of information open in decision cycle. The first (mental approach to acting) is procured by its own knowledge, and the ensuing one (social approach to acting) is the experience obtained from the neighbors, or if nothing else, they endeavored the genuine choices and have the data which choices their neighbors have outstand up until this point and how certain the best illustration of choices was. PSO has been used dynamically as a result of its couple of advantages like strength, capability and straightforwardness. At the point when differentiated and other stochastic estimations it has been found that PSO requires less computational effort [3] [4]. Regardless of the way that PSO has shown its conceivable on various plots for dealing with different headway issues, it really requires amazing execution time to find deals with colossal extension planning issues [5][6].

Related Study

There are a few examinations in the text which have been arranged to join particle swarm optimization algorithm with different variations of metaheuristics, for example, crossover Molecule Multitude Streamlining with Hereditary Calculation (PSOGA) [3, 4], (PSODE) [5], and Molecule Multitude Streamlining with Subterranean insect Settlement Improvement (PSOACO) [6]. These half and half calculations are pointed toward diminishing the likelihood of catching in nearby ideal. As of late a recently nature roused enhancement method is begun, in particular, GSA [7]. The different kinds of mixture variation of Molecule Multitude Advancement had been talked about beneath.

Ahmed et al. [8] introduced half breed variation of PSO called HPSOM. The principal thought of the HPSOM was to coordinate the particle swarm (PSO) with (GA) change procedure. The exhibition of the mixture variation is tried on a few quantities of old style capacities and, based on results got, writers have shown that cross breed variation beats fundamentally the Molecule Multitude Streamlining variation as far as arrangement quality, arrangement solidness, combination speed, and capacity to see as the worldwide ideal.

Mirjalil [10] recently crossover populace based algorithm (PSOGSA) was proposed with the blend of PSO and Gravitational search algorithm (GSA). The principal thought is to coordinate the ability of abuse in Molecule Multitude Improvement with the capacity of investigation in Attractive energy Search Calculation to orchestrate the two variations' solidarity. The presentation of crossover variation was tried on a few quantities of benchmark capacities. Based on results got, creators have demonstrated that the crossover variation has a superior capacity to escape from neighborhood ideal states with quicker union than the PSO and GSA.

Zhang. [11] gave a half and half variation joining PSO back-proliferation (BP) variation called PSO-BP calculation. This variation can utilize not just solid worldwide looking through capacity of the PSOA, yet in addition solid neighborhood looking through capacity of the BP calculation. The combination speed and merged precision execution of recently cross breed variation of PSO were tried on a few quantities of old style capacities. Based on trial results, writers have shown that the mixture variation is superior to the BP and Versatile Molecule Multitude Advancement Calculation (APSOA) and BP calculation as far as arrangement quality and combination speed.

Ouyng[12] introduced a mixture PSO variation, which joins the upsides of PSO and Nelder-Mead Simplex Strategy (SM) variation, is advanced to tackle frameworks of nonlinear conditions, and can be utilized to conquer the trouble in choosing great starting estimate for SM and mistake of PSO because of being effortlessly caught into nearby ideal.

Exploratory outcomes show that the half breed variation has accuracy, high union rate, and incredible power and it can give reasonable aftereffects of nonlinear conditions.

Yu. [13] proposed an original calculation, HPSO-DE, by fostering a reasonable boundary among PSO and DE. This nature of this cross breed variation has been tried on a few quantities of benchmark capacities. In correlation with the Molecule Multitude Streamlining, Differential Advancement, and HPSO-DE variations, the recently crossover variation finds better quality arrangements all the more regularly, is more powerful in getting better quality arrangements, and works in a more viable way.

Grey wolf optimisation is as of late evolved metaheuristics propelled from the hunting system and authority ordered progression of dark wolves in nature and has been effectively applied for tackling enhancing key qualities in the cryptography calculations [15], highlight subset determination, time anticipating, ideal power stream issue [18], monetary dispatch issues [17], stream shop booking issue, and ideal plan of twofold layer frameworks [19]. A few calculations have likewise been created to further develop the intermingling execution of Dark Wolf Enhancer that incorporates parallelized GWO double GWO, joining of DE with GWO], half and half GWO with Genetic Calculation (GA), cross breed DE with GWO and mixture Grey Wolf Streamlining agent utilizing Tip top Resistance Based Learning Procedure and Simplex Technique [28].

Mittal [29] fostered a changed variation of the GWO called adjusted grey Wolf Enhancer (mGWO). A remarkable rot work is utilized to work on the double-dealing and investigation in the hunt space throughout the span of ages. Based on the acquired outcomes, creators demonstrated that the adjusted variation benefits from high investigation in contrast with the standard. Grey Wolf Analyzer and the presentation of the variation is confirmed on a few quantities of standard benchmark and genuine NP difficult issues.

S. Singh [30] present a recently changed approach of GWO called (MGWO). This approach has been begun by altering the position update (surrounding conduct) conditions of GWO. MGWO approach has been tried on different standard benchmark capacities and the precision of existing methodology has additionally been confirmed with PSO and GWO. What's more, creators have likewise thought to be five datasets grouping that have been used to really take a look at the precision of the changed variation. The got results are contrasted and the outcomes utilizing various metaheuristic approaches, or at least, (PBIL), (ACO, etc. Based on factual outcomes, it has been seen that the altered variation can find best arrangements as far as elevated degree of exactness in characterization and further developed nearby optima evasion.

J. H. Holland [32] introduced the different essentials of the hereditary calculation and gave a proper setting to the troublesome enhancement issues portrayed by the combination of (1) significant intricacy and starting vulnerability, (2) the need of securing new data quickly to lessen the vulnerability, and (3) a prerequisite that the new data be taken advantage of as gained so that typical presentation increments at a rate predictable with the pace of obtaining of data.

Nadia Nedjah, et al [34] introduced probably the most imaginative and fascinating applications and increments to the approach and hypothesis of multi-objective multitude knowledge — the impersonation of social multitudes ways of behaving for the arrangement of streamlining issues regarding numerous measures.

A. Kumar et al [35] shown a near report which shows that the HPSO yields further developed execution as far as quicker, developed, and exact limitation when contrasted with worldwide best (gbest) PSO. The presentation results on exploratory sensor network information exhibit the adequacy of the proposed calculations by contrasting the exhibition as far as the quantity of hubs restricted, limitation precision and calculation time.

O. Maimon et al [37] introduced a hereditary calculation way to deal with the part exchanging issue. The effortlessness and strength made GA appealing particularly when it is joined with present day figuring power. This approach can manage 'look-ahead' thought of part switches, consequently rising above the inconvenience of decoupling the PCB sequencing sub-issue from the part stacking sub-issue.

Proposed System

1. Architecture of Proposed Work

This part makes sense of about exhaustively of all the Multitude based improvement calculations which are presented in this paper. Design of the proposed framework is displayed in the underneath figure. Here input is different datasets are thinking about in this paper utilized three different datasets (Bosom Disease, diabetes and liver). Subsequent stage is advancing the brain organization and preparing the organization with most well known enhancement calculations to get sensible precision.

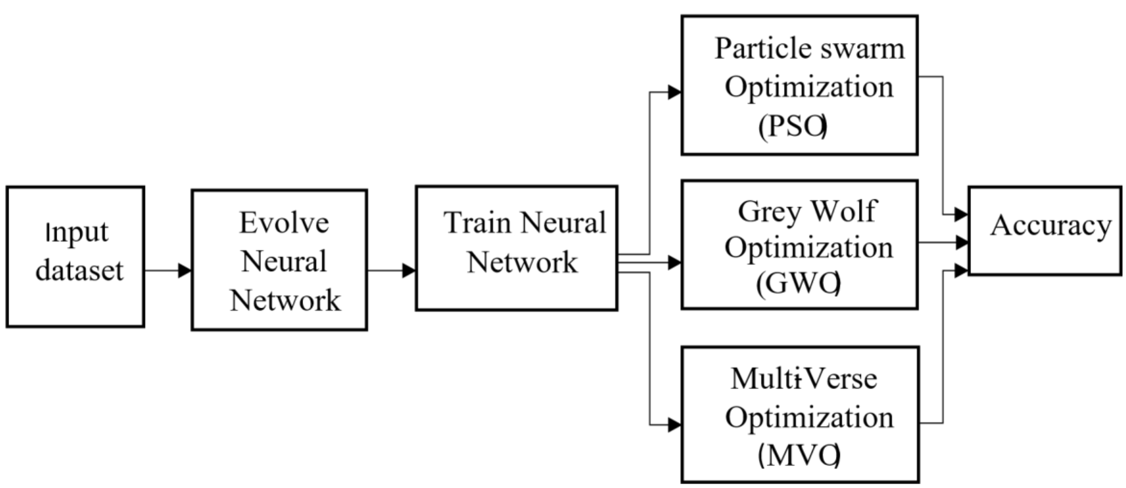


Figure 1 Proposed Architecture

The basic diagram of neural network is shown in below:

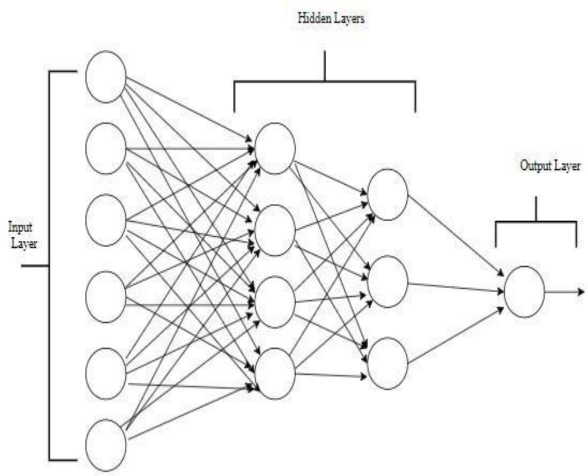


Figure 2 Basic Neural Network

Left most layer from the neural network architecture is called as input layer and the right most layer is called as output layer and middle layers is/ are called as hidden layers. The above shown neural network consists of two hidden layers. The following optimization algorithms are used to train the neural network.

Particle Swarm Optimization (PSO) Algorithm

Particle Swarm optimization is propelled by bird rushing and tutoring. This calculation is the absolute first and fundamental streamlining calculation and extremely basic calculation. A gathering of factors which will likewise have their singular qualities change nearer to the factors which is close or nearest to the objective variable at that current second. For instance, picture there are gathering of birds and furthermore food is accessible somewhere near them.

First the bird which is close to the food will make a sound with the goal that others can make a way to arrive at the food. In light of the sound the birds will make a most limited way tom arrive at the food. This is the basic illustration of molecule swarm improvement.

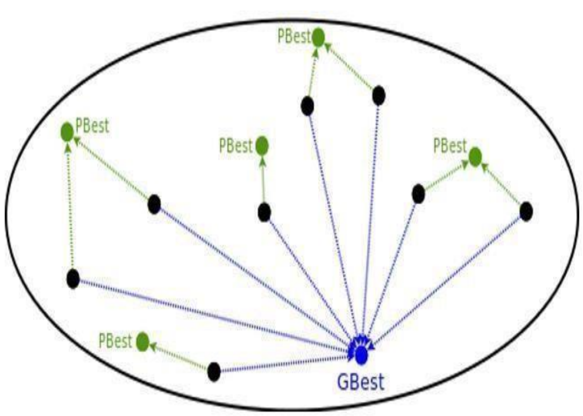


Figure 3 Movements of particles in PSO

Mainly the PSO algorithm will keep track of following variables:

1. Target condition or value
2. gBest(Global best) values, This holds the value(data) of particle which is closest to the target.
3. Stopping condition when the algorithm not found the target.

PSO is instated with a social occasion of sporadic particles (game plans) and a short time later searches for optima by reviving ages. In each cycle, each particle is revived by following two "best" values. The first is the best course of action (wellbeing) it has achieved up until this point. (The health regard is similarly taken care of.) This value is called pbest. Another "best" regard that is trailed by the particle swarm analyzer is the best worth, gained so far by any atom in the general population. This best worth is an overall best and called gbest. Right when a particle eliminates a piece of the general population as its topological neighbors, the best worth is a close by best and is called lbest.

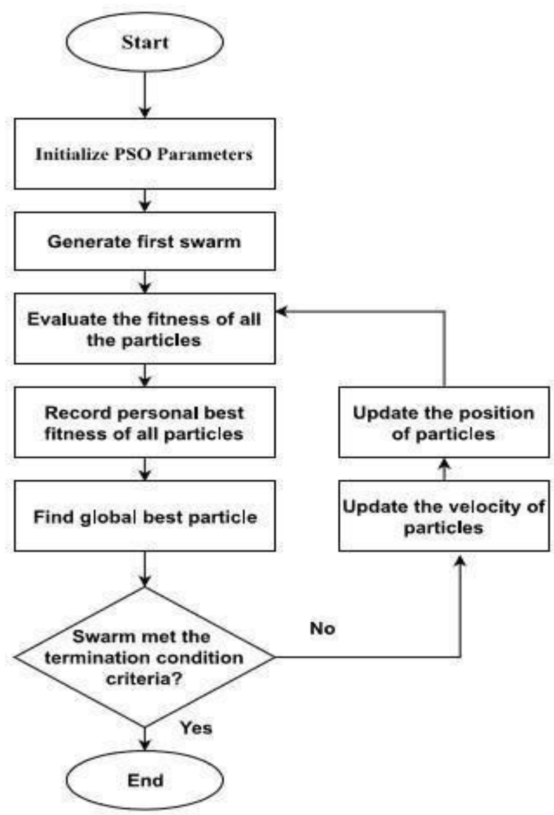


Figure 4 Flow Chart of Particle Swarm Optimization

Every particle contains:

1. Velocity value, indicates how much data can be modified.
2. data, indicates possible solution
3. pBest(personal best) value, this holds the value particle has ever come to the target.

Pseudocode

```
Begin
 t = 0
        Initialize random particles p(t) Evaluate particles p(t)
        while(!stop_condition) Begin
                t = t +1   update weights
                select pBest for each particle          select gBest for each particle
        p(t-1)  calculate velocity of particle p(t)     update velocity and position of
        particle p(t)        evaluate best particle value (fitness) end
end
```

After finding the two best values, the particle updates its velocity and positions with following equation:

$$(t + 1) = w * (t) + c_1 * r_1[xp_i(t) - x_i(t)] + c_2 * r_2[xg_i(t) - x_i(t)] \quad \text{----- (1)}$$

$$(t + 1) = (t) + (t + 1) \quad \text{------(2)}$$

Where,
w is the inertial coefficient
r_1 and r_2 are random numbers between 0 and 1
c_1 and c_2 are learning factors (usually these values considered as 2)
(t) is the particle's velocity at time t
$(t + 1)$ is the particle's velocity at time t+1
(t) is the particle's individual best value at time t
(t) is the particle's position at time t
(t) is the particle's global best solution at time t
$(t + 1)$ is the particle's position at time t

Every Particle Contains

1. Velocity value indicates how much data can be modified.
2. data, indicates possible solution
3. pBest(personal best) value, this holds the value particle has ever come to the target.

The adaptive formula for inertial coefficient is given below:

W= W Max-t *(wMax-wMin)/T. ------(3)

Where,

T is the total number of iterations

t is the current iteration

Grey Wolf Optimization (GWO) Algorithm

Grey Wolf Optimization (GWO) calculation is a meta-heuristic populace based calculation. This algorithm work with alpha, beta, delta and omega. They work with fittest solution.

Alpha-First Fittest Solution

Beta-Second Fittest Solution

Delta-Third Fittest Solution

omega-Fourth Fittest Solution

The social hierarchy of are wolfs are shown in bellow figure.

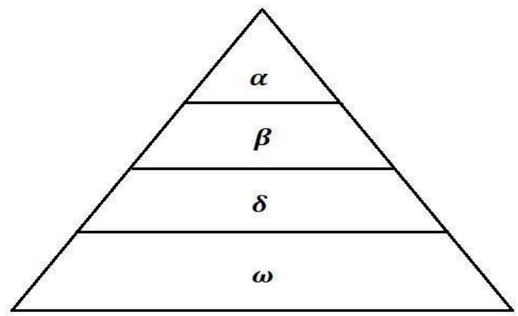


Figure 5 Leadership hierarchy of wolves

The main phases of grey wolves hunting are:

1. Tracking, chasing, and approaching the prey.
2. Pursuing, encircling, and harassing the prey until it stops moving.
3. Attacking towards the prey

The diagram representation of the grey wolves movements and the parameter representation are shown in the bellow figure:

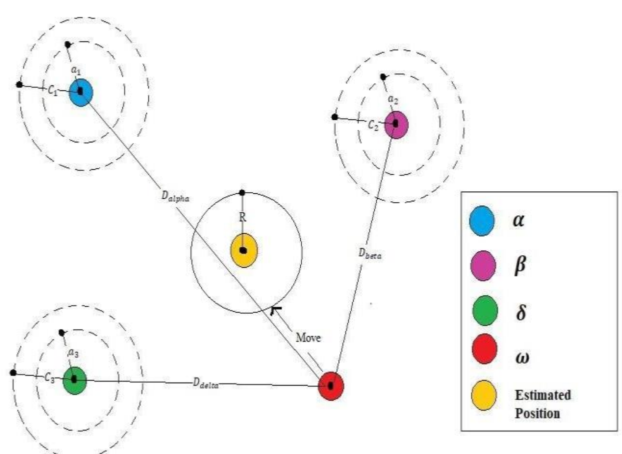


Figure 6-Diagram representation of grey wolves

Mathematical Design and Algorithm

The mathematical design will consist of four parts. They are,

1. Social hierarchy
2. Tracking
3. Encircling and
4. Attacking prey

The equations for encircling behavior of the grey wolves is given bellow:

$$\vec{D} = |\vec{C}.\vec{x}_p(t) - x(t)| \quad (4)$$

$$x(t+1) = \vec{x}_p(t) - A.\vec{D} \quad (5)$$

Where, t is current iteration, A and C are coefficient vectors, x (t) indicates position vector of grey wolf, $\vec{x}_p(t)$ indicates position vector of prey.

The vectors A and C are calculated as follows:

$$A = 2a.\vec{r}_1 - a \quad (6)$$

$$C = 2.\vec{r}_2 \quad (7)$$

Where,

Components of a are linearly decreased from 2 to 0 over the iterations r_1 and r_2 are random vectors [0,1].

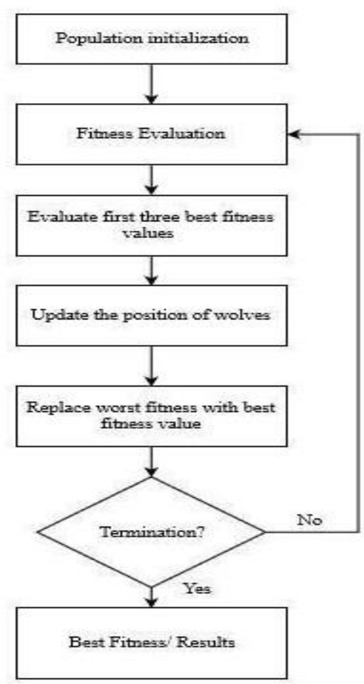


Figure 7 Flow chart of Grey Wolf Optimization (GWO)

The adaptive formula for 'a' is given as:

a=2-t*2/T. -------(8)

Iterations

Alpha, Beta and Delta are the first three best solutions that are considered in this paper.

To update their positions the equations are given bellow:

$$\vec{D}\alpha = |\vec{C}1.\vec{X}\alpha - X| \quad \text{--------(9)}$$

$$\vec{D}\beta = |\vec{C}2.\vec{X}\beta - X| \quad \text{------(10)}$$

$$\vec{D}\delta = |\vec{C}3.\vec{X}\delta - X| \quad \text{-------(11)}$$

$$\vec{X}1 = \vec{X}\alpha - \vec{A}1.(\vec{D}\alpha) \quad \text{------(12)}$$

$$\vec{X}2 = \vec{X}\beta - \vec{A}2.(\vec{D}\beta) \quad \text{------(13)}$$

$$\vec{X}3 = \vec{X}\delta - \vec{A}3.(\vec{D}\delta) \quad \text{------(14)}$$

X(t+1)=X1+X2+X3/3. -----(15)

Pseudocode

Begin

Initialize n population of gray wolves and positions randomly
while(!termination_condition) for each wolf update the current wolf location
end evaluate the
fitness of all wolves update alpha, A and
C
Evaluate the individual positions of wolves update alpha, beta and
delta end

Multi-Verse Optimization (MVO) Algorithm

Multi-Verse is a theory which is states that there might be many different physical laws in every universe. Multi-Verse theory is the inspiration of the Multi-Verse Optimization (MVO) Algorithm.

The three main concepts of Multi-verse are:

1. Black hole
2. White Hole
3. Worm hole

These are the conceptual components of Multi-Verse Optimization (MVO)

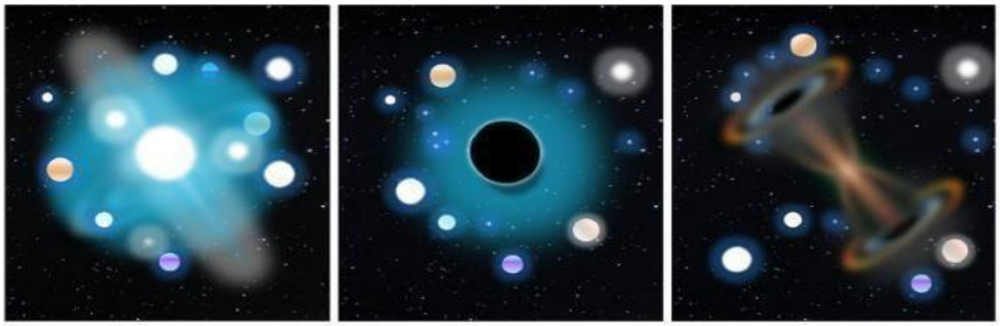


Figure 4.8 White Hole, Black Hole and Wormhole

While doing optimization, the following rules are applicable to the universes of MultiVerse Optimization:

1. They are undetectable. Space telescopes with exceptional apparatuses can help discover Black Holes. The exceptional devices can perceive how stars that are near Black Hole act uniquely in contrast to different stars.
2. White hole is exactly opposite to the black hole.
3. hole is an entity allowed by Einstein's Theory of General Relativity in which two distant times (or locations) are connected by space time curvature. Worm hole is also known as EinsteinRosen Bridge or Schwarzschild wormhole, Lorentzian wormhole, Morris-Thorne wormhole. Black holes are very dangerous because when it collapses emits a high radiation and dangerous contact with exotic matter.

Pseudocode

```
Create random universe(U)
Initialize WER, TDR and Best_Universe
While(!stop_condition)
        Evaluate fitness of all universes
        For i in universe
                Update WEP and TDP
                Black_Hole_index = i            For j in universe
                        if (RouletteWheelSelection)
                sort the universes
                        end
        if
                                update the universes
                end             end
        end
```

To represent the numerical model we assume that,

U=[xn1 xn2. …xnd]. ------(16)

Where,

D is the number of parameters (variables) and n is the number

Xi={xj+TDR*((ubj-lbj)*(r4+lbj))<rWEP. ------(18)

of universes (candidate solutions):

Xij{xjk r1<N1(Ui). ------(17)

Where,

Where,

TDR and WEP are coefficients, Xj shows jth boundary of best universe framed up until this point, ubj is upper bound of jth variable, lbj is lower bound of jth variable, xij demonstrates jth boundary of ith universe, and $r2$, $r3$ are arbitrary numbers [0,1].

It could be derived from the pseudocodes and numerical definition that there are two primary coefficients thus: wormhole presence likelihood (WEP) and voyaging distance rate (TDR).

The versatile recipe for the two coefficients is as per the following:

WEP=min+l*(max-min)/L. ------(19)

Where, min indicates minimum (min=0.2 in this paper),

max indicates (max=1 in this paper), l indicates current iteration, and L is maximum iterations.

TDR=(1-L1/P)/L. -------(20)

Where, p is the exploitation accuracy over iterations (p=6 in this paper), p is directly proportional to the accuracy of exploitation/ local search.

Table 1. Analysing CPU process Time

		Avg. CPU time per trial				**Avg. CPU time per iteration**		
Sample	GA	PSO	GWO	MVO	GA	PSO	GWO	MVO
1	168	228	600	495	0.09	0.13	4.78	0.25
2	329	403	600	600	0.16	0.22	10.78	0.31
3	439	534	600	600	0.22	0.27	19.37	0.41
4	426	540	600	600	0.20	0.27	23.32	0.43
5	412	545	600	600	0.19	0.27	25.06	0.45
6	478	600	600	600	0.23	0.32	33.05	0.54
7	495	601	600	600	0.24	0.33	35.85	0.50
8	585	600	600	600	0.31	0.42	49.72	0.68

TABLE 2: QAP AT DIFFERENT PROBLEMS SIZE

Problem Name	Problem Size	Best Known Quality
P1	28	70986
P2	13	1156
P3	16	9896
P4	129	641
P5	17	141
P6	32	438
P7	65	128
P8	12	1652
P9	15	2724
P10	21	6922
P11	31	91420
P12	36	9526

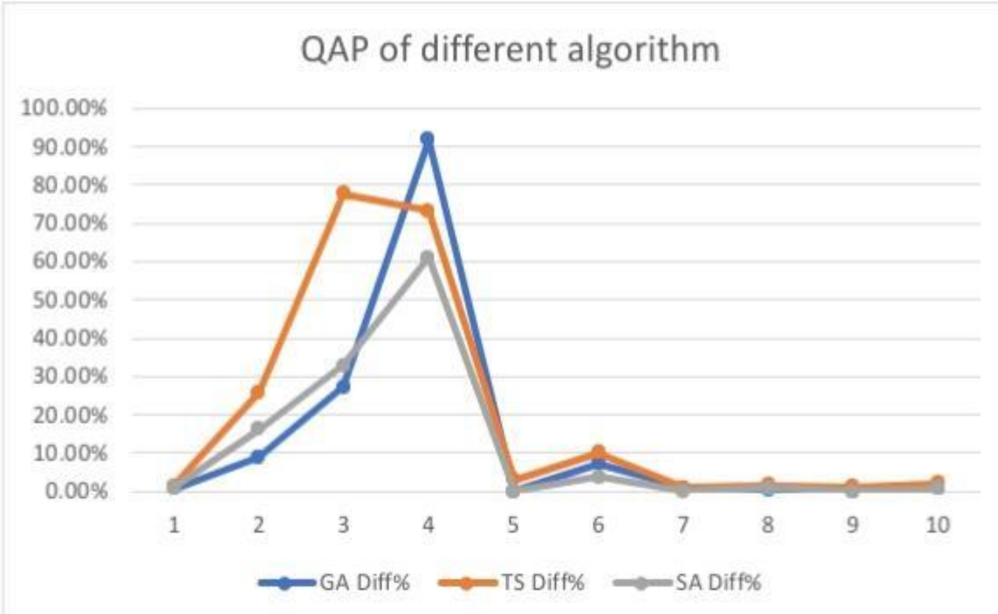
The acquired Best quality output for every calculation of Meta-heuristic calculations are contrasted and QAPLIB Most popular Quality arrangements. For every issue occasion we execute a progression of runs for different boundaries.

Relative distinction addresses the contrast between calculation best quality arrangement and the most popular quality arrangement of the issue in percent. The distinction esteem is determined in the accompanying manner.

Relative difference= ((Best Quality − Best Known Quality) / Best Known Quality) * 100%

TABLE 3: RELATIVE DIFFERENCE OF THE SOLUTION QUALITY FOR QAP AT DIFFERENT PROBLEMS SIZE

Sample	GA Diff%	TS Diff%	SA Diff%
P1	0.95%	1.71%	0.97%
P2	9%	25.91%	18.22%
P3	29.21%	79.66%	32.95%
P4	93.67%	76.26%	62.94%
P5	0%	4%	0%
P6	8.13%	12.13%	2.88%
P7	3%	2.07%	0%
P8	0.73%	1.70%	0.87%
P9	0%	1.31%	0%
P10	0.973%	2.23%	0.82%



Regarding the execution time, in table 3 we take a gander at the execution time by each computation for QAP at different issues size. Execution time in the association (minutes: seconds. tenths of seconds).

TABLE 4. SOLUTION EXECUTION TIME FOR QAP AT DIFFERENT PROBLEMS SIZE

Problem Name	**Execution Time** GWOA	**Execution Time** PSOA	**Execution Time** MOA
P1	00:10.4	00:00.4	00:02.7
P2	00:08.9	00:00.1	00:02.3
P3	00:08.6	00:00.2	00:02.5
P4	00:33.6	00:17.8	00:13.7
P5	00:10.0	00:00.1	00:03.6
P6	00:10.2	00:00.4	00:03.3
P7	00:15.4	00:01.6	00:04.9
P8	00:08.6	00:00.2	00:02.4
P9	00:08.7	00:00.2	00:02.4
P10	00:09.0	00:00.3	00:02.5

RESULTS COMPARISON

Before Tuning:

Training Dataset:

Table 5: Comparison of Optimizers training data without tuning the parameters

Optimizer	Dataset	Train TP	Train FN	TrainFP	TrainTN	Train_Accuracy
PSO	BreastCancer	300	1	119	41	0.7396
	Diabetes	30	142	45	289	0.6304
	Liver	0	95	1	131	0.5771
GWO	BreastCancer	288	13	19	141	0.9305
	Diabetes	56	116	84	250	0.6047
	Liver	47	48	21	111	0.6960
MVO	BreastCancer	288	13	7	153	0.9566
	Diabetes	88	84	29	305	0.7766
	Liver	54	41	20	112	0.7312

Testing Dataset:

Table 6: Comparison of Optimizers testing data without tuning the Parameters

Optimizer	Dataset	Train TP	Train FN	TrainFP	Train TN	Train_Accuracy
PSO	BreastCancer	157	0	61	20	0.7436
	Diabetes	23	73	25	141	0.6259
	Liver	0	50	0	68	0.5762
GWO	BreastCancer	155	2	5	76	0.9705
	Diabetes	28	68	36	130	0.6030
	Liver	32	18	9	59	0.7711
MVO	BreastCancer	153	4	3	78	0.9705
	Diabetes	46	50	18	148	0.7404
	Liver	33	17	12	56	0.7542

Parameters After Tuning:

Training Dataset:

Table 7: Comparison of Optimizers training data with tuning the parameters

Optimizer	Dataset	TrainTP	TrainFN	TrainFP	TrainTN	Train_Accuracy
PSO	BreastCancer	284	17	5	155	0.9522
	Diabetes	90	82	29	305	0.7806
	Liver	48	47	16	116	0.7224
GWO	BreastCancer	288	13	6	154	0.9587
	Diabetes	87	85	28	306	0.7766
	Liver	50	45	23	109	0.7004
MVO	BreastCancer	289	12	5	155	0.9631
	Diabetes	90	82	33	301	0.7727
	Liver	51	44	19	113	0.7224

Testing Dataset:

Table 8: Comparison of Optimizers testing data with tuning the parameters

Optimizer	Dataset	TestTP	TestFN	TestFP	TestTN	Test_Accuracy
PSO	BreastCancer	155	2	2	79	0.9831
	Diabetes	45	51	19	147	0.7328
	Liver	29	21	11	57	0.7288
GWO	BreastCancer	153	4	2	79	0.9747
	Diabetes	48	48	18	148	0.7480
	Liver	32	18	13	55	0.7372
MVO	BreastCancer	152	5	1	80	0.9831
	Diabetes	49	47	16	150	0.7595
	Liver	34	16	11	57	0.7711

Conclusion

In this proposed paper, three swarm based were presented, namely Particle Swarm Optimization (PSO), (MVO) and (GWO). A brief overview of each algorithm is presented along with flow charts, pseudocode to implement the models. The performance of each algorithm is compared with other by applying different datasets. Multi-Verse Optimization Algorithm will give best fitness and accuracy values than other optimization algorithms. In future this can be extended by using latest optimization algorithms with more latest tuning parameters techniques to improve the performance of the algorithms.

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