PalArch's Journal of Archaeology of Egypt / Egyptology

SOLVING SINGLE OBJECTIVE PRODUCTION PLANNING PROBLEM BASED ON MOGSA ALGORITHM AND TOPSIS TECHNIQUE

Iraq.T.Abbas

University of Baghdad, College of Science, Department of Mathematics.

Iraq.T.Abbas , Solving Single Objective Production Planning Problem Based On Mogsa Algorithm And Topsis Technique , Palarch's Journal Of Archaeology Of Egypt/Egyptology 18(7). ISSN 1567-214x.

Abstract:

On various benchmarks and real-world multi-objective optimisation concerns, multi-objective evolutionary algorithms have proven to be well implemented. However, MOEAs could have several trouble solving thousands of variables for large data optimization problems. The first scenario presents a new technique based on the multi-objective gravity search algorithm GSA, to resolve a single-objective optimisation problem based on the parameter 0 to 1 in order to fix the problem this survey suggests the scenario: a single objective gravity search algorithm, multi-objective gravitational search algorithm and a simulation. The absence of a nearby inquiry system raises the strengthening of search, although the diversity remains high and easily configured. MOGSA is evaluated using the three-part evaluation technique (1) describesMOGSA's benchmarking (unconstrained), in order to determine the algorithm's efficiency, (3) evaluate the algorithm performance using mean, standard deviations, point of the MOGS, and (3) evaluate the algorithm. The findings and the discussion of optimizations confirm that the MOGSA algorithm is competing well with state-of-the-art meta-heuristic and standard approaches. Main Words: algorithms for Meta-Heuristic, BAT, TOPSIS and GSA algorithms.

1. Introduction:

Due to the exponentially expanded problem-size search space, classical optimization algorithms do not have the sufficient approach to optimization problems with a highly dimensioned search field. It is also not possible, such as systematic analysis, to overcome such problems by using exact techniques.

Natural computation has attracted a great deal of interest among researchers over the past two decades to create counterfeit figuring frameworks that tackle numerous complex numerical issues, nature is a significant wellspring of standards, systems and thoughts. Individually, their races' sustainability and long-term preservation must be suited to their climate. This process is referred to as creation. Maintaining the reproductive period may also maintain the features which encourage individuals' competitiveness and eradicate their weaknesses. Just the good citizens among the surviving population will transmission their offspring with genetically modified genes. Transformative calculations which are perhaps the most widely recognized and productive exploration calculations, have motivated this technique, known as natural selection.

1.1 Gravitational Search Algorithm (GSA)

The rotation and gravity laws of Newton were applied in the new algorithm. It is utilized in various applications that adjust the technique utilized in the gravity calculation[1]. However, a lot of study has exposed the algorithm as unclear. The inertial weight, position, active weight and passive gravitational mass can be regarded in the GSA as the four parameters for each of the masses (agent).The mass location correlates (first) to better BAT behaviour in the event of big crises, and (second) to increasing the diversity of the population of BAT in order to deter local Optima from being caught in it. In comparison, the downside is that the algorithm intensification is not quite diverse relative to it. (The accompanying pseudo code).

Pseudo code for Gravitational Search algorithm

```
Initialization( );
T = 1;
While t < max.no.of iteration;
Evaluate Fitness of each particle;
Update the mass of moving particles ();
Update particles acceleration ();
Update particles velocity ();
Update and mutate particles positions ();
T = t + 1;
End while;
```

End

1.2 Bat Algorithm (BAT)

The BAT algorithm proposed to be newly optimized, [2] based on swarm intelligence and bats' behavior. BAT can be used to mimic aspects of the echolocation properties of a microbat. The BAT Algorithm is simple to implement, scalable and easy. It effectively solves a wide range of problems and provides promising optimum solutions, particularly highly nonlinear issues. BAT performs well in tough conditions and provides a simple MOGS solution. The following drawbacks are nevertheless present. The rate of convergence is early and slows down. The parameters are related to the convergence rates, not doing a statistical analysis. The MOGS values for most applications are still not attained. (Bat algorithm as illustrated below).

Pseudo code for Bat algorithm

Objective function f (x), $x = (x1, \dots, xd)^T$
Set the population of batx_i $(i = 1,2, \dots, n)$ and v_i
Establish the frequency of pulsationf_i at x_i
Begin pulsation frequenciesr_i and the loudness A_i
while (t $< Max\ number\ of\ iterations$)
Build new solutions with frequency change,
Modified speeds and settings [see Yang equations (2010)]
if (rand $> r_i$)
From MOGS solutions, pick a solution
Generate a local solution to the chosen MOGS solution
Terminate if
Spontaneously fly to create a new approach
if (rand $< A_i$& f $(x_i) < f$ (x^*))
Accept the emerging solutions
Increase r_i and reduce A_i
end if
Rundown the bats and locate the current onesMOGSx^*
finish while

End

1.3 Proposed Multi-Objective Algorithm (MOGSA)

Centred on the improvement of the original swarm intelligent algorithms, the multi-objective optimization algorithm suggested in this study is structured. The researcher made two improvements. The first improvement is approach to the optimal solution, which is achieved by the counter by selecting GSA. The present study implements this improvement to accelerate the process of approaching solution by applying GSA if the random number γ is less than 0.5 (because it leads to increased diversification and decrease intensification) [2]. For the MOGS solution, access speed is improved to use the comparable speed of the initial BAT (because each algorithm is working correctly if they make balancing between the diversification and intensification). The second improvement depends on the basis of the search in the early exploration process of the solution; the present study updates all the solutions in population to increase the intermingling rate before the finish of the proposed calculation. Test the precision, intermingling, and speed of the moved toward convention utilizing a sum of 23 benchmark capacities. MOGSA is intended to settle a solitary goal for an unconstrained improvement issue. In this manner, it opens up two unmistakable pathways in similar territory between various settings, which is clarified in detail as follows.

MOGSA Procedure
Set $k = 0$, velocity $= 0$ and $\beta = 0.7$;
Input GSA and BAT parameter r^0, A ;
Random initialize point P_i for n population;
Calculate the fitness value of initial population ;
While (the termination condition are not met)
If rand $< \beta$
1) **GSA setup**
Calculate the mass function **m**
Calculate the gravitational constant **G**
Calculate the acceleration in gravitational field **a**
$V_{t+1} = \text{rand} * V_t + a$
$P_{t+1} = P_t + V_{t+1}$
Else
2) **Bat setup**
$Q = Q_{min} + (Q_{min} - Q_{max}) * \text{rand}$
$V_{t+1} = V_t + (P_{best} - P_t) * Q$
$P_{new} = P_t + V_{t+1}$
If rand $> r$
$P_{new} = P_t + \text{rand}\,(P_{t+1} - P_t)$
End f

If $f(P_{new}) \leq f(P_t)$ and (rand $< A$)
$P_{new} = P_t$
End f
3) U**pdate all solutions in population**
For (each point i in the population)
$c = \text{rand int}(1,2)$
$P_{new} = P_i + \text{rand}\,(P_{t+1} - c * \overline{P})$
If $f(P_{new}) \leq f(P_i)$
$P_{best} = P_{new}$
End f
End for
End While

The new multi-objective algorithm works as follows. First, the present study inputs GSA and BAT parameters r^0, A_i, and then randomly initialize point P_i. The present study calculates the fitness values f(p) of the initial population.On the off chance that the rand (irregular number) is lower than the boundary (e.g., γ=0.5), so GSA is performed by the researcher. In the gravitational field a, the mass function m, gravitational constant G, velocity V(t+1) and position P((t+1)) are measured for processing diversity and acceleration. [1].MOGSAafter operating on one algorithm after another, in order to overcome the bugs in both, you'll associate the two zones in a similar locale (for example from a similar room in multitude insight). The next step is the modernization of all category solutions based on the following equation: $P_{new} = P_i + rand * (P_{best} - c * \overline{P})$. All solutions in the population are modified in the next stage and this update relies on the specified equation.

1.4 Methodology of Examination, Outcomes and Discussion:

The efficiency of the MOGSA algorithm proposed is evaluated in this section. Firstly, the assessment approach is defined and the results of the experiments performed in three scenarios with separate optimization problems are discussed. Second, the efficiency of the MOGSA algorithm is contrasted with that of other advanced computational techniques (GSA, original BAT, and PSO). Third, our observations are explored in depth.

In the next segment, experimental comparison is made. The present research presents simulation findings in terms of solution performance, convergence capacity, and precision by comparing MOGSA to primary. The standard Tarasewich benchmark functions [3] (i.e., test functions = 23) and [4] executed in this segment are utilized to test the union and consistency of MOGSA along these lines. In a similar climate, the standard BAT and standard GSA are thought about; in a similar setting, our multi-target calculation is contrasted by the agent and the standard PSO. The objective of improvement is to limit the entirety of the benchmarks thus. For all the calculations in the analyses, the populace size is set as 100 (N=100), i.e. MOGSA, PSO original, GA, GSA heart, and BAT original. See[5] for explanations of the PSO parameter settings, as well as the BAT, GA and GSA settings, refer to [2], [6] and [1], respectively.

1.5 Methodology of Analysis:

The technique of assessment employed in this work is split into three sections. The first section explains MOGSA's (unconstrained) benchmarking of the topic of optimization to test the unwavering quality of the proposed calculation MOGSA. The subsequent segment differentiates the effectiveness of the MOGSA algorithm with that of other numerical algorithms that are intelligent. In the third section, the protocol of the proposed MOGSA algorithm is explained.

1.5.1 Benchmarking of the Problem of Optimization (unconstrained)

For any method, according to no free lunch (NFL) theorem[7], any raised yield more than one bunch of issues is exactly made up for in execution over another class. A certain meta-heuristic may yield promising outcomes on a progression of issues, however may perform inadequately on another arrangement of issues. In the NFL, this field of examination is particularly fruitful. As a consequence, the existing approaches are reinforced and every year new meta-heuristics are suggested.

1.5.1.1 Unconstrained optimisation problem:

Table I uses 23 default benchmarks that can be divided the capacities are single-modular (F1 to F7), multimodal (F8 to F13) and multimodal (F14 to F23). In literature, these benchmark functions have been commonly used[8].

Unimodal characteristics efficiently overcome the problems by applying deterministic improvement calculations that utilization angle data. In any case, see capacities were basically used to evaluate the combination paces of EAs. High-dimensional multi-modular capacities, then, have numerous neighbourhood essentials and are difficult to improve. The ultimate results are significant on the grounds that they address the calculation's capacity to escape from a disagreeable nearby ideal and locate a close worldwide ideal. We perform F8 to F13 tests where the quantity of nearby locales is indicated. The measurements of the chosen size are comparatively lower (30, 100, 200 and 300). The benchmark characteristics of F14 to F23 are low-dimensional non-modal (Title 6) and have very few local minima's in low-dimensional Multi-Modal functions. This set of characteristics is not as complex as a set of multimodal characteristics with many local minima (F8 to F13). By using deterministic algorithms, in truth, some of these functions can also be efficiently solved.

Table 1: Sets of common benchmark unconstrained functions

Test Function	n	S	f_{min}
$F_1(x) = \sum_{i=1}^{n} {x_i}^2$	[30,100, 200, 300]	[−100,100]	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[30,100, 200, 300]	[−10,10]	0
$F_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{i} x_j)^2$	[30,100, 200, 300]	[−100,100]	0
$F_4(x) = \max_i\{\lvert x_i \rvert, 1 \le i \le n\}$	[30,100, 200, 300]	[−100,100]	0
$F_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - {x_i}^2)^2 + (x_i - 1)^2]$	[30,100, 200, 300]	[−30,30]	0
$F_6(x) = \sum_{i=1}^{n} [(x_i + 0.5)^2]$	[30,100, 200, 300]	[−100,100]	0
$F_7(x) = \sum_{i=1}^{n} i{x_i}^4 + \mathrm{random}(0,1)$	[30,100, 200, 300]	[−1.28,1.28]	0

$F_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\lvert x_i \rvert}$	[30,100, 200, 300]	$[-500,500]$	-12,569.487, -41898.29,-83793.33,−125694.7
$F_9(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i)+10]$	[30,100, 200, 300]	$[-5.12,5.12]$	0
$F_{10}(x) = 20\exp\left(-0.2\sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}}\right) - \exp\left(\frac{\cos(2\pi x_i)}{n}\right) + 20 + e$	[30,100, 200, 300]	$[-32,32]$	0
$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{i}\right) + 1$	[30,100, 200, 300]	$[-600,600]$	0
$F_{12}(x) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10,100,4)$ $y_i = 1 + \frac{x_i + 1}{4} u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m x_i > a \\ 0 \quad -a < x_i < a \\ k(-x_i - a)^m x_i < -a \end{cases}$	[30,100, 200, 300]	$[-50, 50]$	0

$F_{13}(x) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2[1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5,100,4)$	[30,100, 200, 300]	$[-50, 50]$	0
$F_{14}(x) = \left[\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j + \sum_{i=1}^{2}(x_i - a_{i,j})^6}\right]^{-1}$	2	$[-65.536, 65.536]$	1
$F_{15}(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^2$	4	$[-5, 5]$	0.0003075
$F_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4$	2	$[-5, 5]$	-1.0316285
$F_{17}(x) = \left(x_2 - \frac{5.1}{2\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10$	2	$[-5,10] \times [0,15]$	0.398
$F_{18}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3{x_1}^2 - 14x_2 + 6x_1x_2 + 3{x_2}^2)] \times [30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12{x_1}^2 + 48x_2 - 36x_1x_2 + 27{x_2}^2)]$	2	[-2,2]	3
$F_{19}(x) = -\sum_{i=1}^{4} c_i \exp\left[-\sum_{j=1}^{4} a_{i,j}\left(x_j - p_{i,j}\right)^2\right]$	3	[0,1]	-3.86

$F_{20}(x) = -\sum_{i=1}^{4} c_i \exp[-\sum_{j=1}^{6} a_{i,j}(x_j - p_{i,j})^2]$	6	[0,1]	-3.32
$F_{21}(x) = \sum_{i=1}^{5} [(x-a_i)(x-a_i)^T + c_i]^{-1}$	4	[0,10]	-10
$F_{22}(x) = \sum_{i=1}^{7} [(x-a_i)(x-a_i)^T + c_i]^{-1}$	4	[0,10]	-10
$F_{23}(x) = \sum_{i=1}^{10} [(x-a_i)(x-a_i)^T + c_i]^{-1}$	4	[0,10]	-10

1.5.2 Comparison of the MOGSA algorithm with other clever strategies for programming and parameter settings:

Table 1 indicates the minimal value distribution for a function; n is the function axis; and S is a subset of R^n addressing the lower and upper qualities. The base estimation of the capacities (f_{opt}) in Table 3.1 is negative in most situations, with the exception of F8, which has a minimum value of -12.569487. Other functions have varying optimal solutions and dimensions, such as F 14 to F 23.With two classes of algorithms, we compare the efficiency of the MOGSA algorithm. Nine algorithms are included in the first category, namely PSO, BAT, and GSA, whose parameter settings are described in Table 2.

Table 2: Settings of the parameters for the type of algorithm used in the analysis

Algorithm	Function
MOGSA	$c_1, c_2, \alpha = 2$, $a = 0.1$,$Pop_{size} = 100$, $A = 1$
PSO	$c1, c2 = 2$, $\omega = 0.4$, $Pop_{size} = 100$
GSA	$Pop_{size} = 100, \alpha = 0.1, G(t) = G_0 e^{-\alpha\frac{t}{T}}$ (a)
BAT	$Pop_{size} = 100$, $w = 0.5$, $c_1 = 1, c_2 = 2$, $a = 0.1$, $A = 0.6, r^0 = 0.5$
GA	crossover and mutation are 0.3 and 0.1

1.6 Results:

The proposed MOGSA algorithm and bench marking functions developed on the basis of three groups of unconstrained optimization problems referred to in section 1 are contrasted with the intelligent computing strategies listed in section 1.2.

For the benchmark functions, three of the above algorithms are implemented and the outcomes for the accompanying cases are unimodal high-dimensional capacities. Single F1 to F7 capacities utilized. The combination pace of the pursuit calculation is a higher priority than the eventual outcomes for single capacities in these circumstances, inferable from execution techniques that streamline single capacities.
More than 20 circles, the impacts are added and the MOGSA, mean, most exceedingly awful and standard deviation boundaries are recorded in the last emphasis for the unimodal capacities portrayed in Table 2.

Table 3: Impact standardization from the MOGSA criteria F_1 to F_7

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_1	0	0	1	0	0.64
F_2	0	0	0	1	0.29
F_3	0	0.01	0	1	0
F_4	0	0	1	0.27	0.29
F_5	0.18	0.21	0	0.12	1
F_6	0	0	0	0	1
F_7	0	0	0.05	0	1
Sum	0.18	0.22	2.05	2.39	4.23
Rank	**1**	2	3	4	5

Table 4: Impact standardization from the MOGSA criteria F_1 to F_7

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_1	0	0	0	0	0
F_2	0	0	0.90	0.01	0
F_3	0	0	2.95	0.65	0
F_4	0	0	1.24	0.05	0.02
F_5	0	0	3.22	0	0
F_6	0	0	0	0	0
F_7	0	0	0.19	0.02	1
Sum	**0**	0.01	8.50	0.74	1.03
Rank	**1**	2	5	3	4

Table 5: Impact standardization from the MOGSA criteria F_1 to F_7

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_1	0	0	1	0	0
F_2	0	0	1	0	0
F_3	0	0	1	0.84	0
F_4	0	0	1	0.07	0.02
F_5	0	0	1	0.01	0
F_6	0	0	1	0	0
F_7	0	0	0.10	0.11	1
Sum	**0**	**0**	6.10	1.02	1.03
Rank	**1**	2	5	3	4

Table 6: Impact standardization from the MOGSA criteria F_8 to F_{13}

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_8	0.20	0.67	0	0	1
F_9	0	0.06	0.11	1.00	0.70
F_{10}	0	0.16	0.51	1.00	0.18
F_{11}	0	1	0	0	0.10
F_{12}	0	0	0	1	0
F_{13}	0	0	0.02	1	0
Sum	0.20	1.89	0.64	4.00	1.98
Rank	**1**	3	2	5	4

Table 7: Impact standardization from the MOGSA criteria F_8 to F_{13}

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_8	0.22	0.72	0	0	1

F_9	0	0.08	0.14	1	0.72
F_{10}	0	0.02	0.46	1.00	0.04
F_{11}	0	0.23	1	0	0.02
F_{12}	0	0	0	1.00	0
F_{13}	0	0	0.05	1	0
Sum	0.22	1.04	1.65	4.00	1.77
Rank	**1**	2	4	5	3

Table 8: Impact standardization from the MOGSA criteria F_8 to F_{13}

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_8	0.24	0.73	0	0	1
F_9	0.00	0.09	0.19	1	0.74
F_{10}	0.27	0	0.49	1	0
F_{11}	0	0.18	1	0	0.01
F_{12}	0	0	0	1	0
F_{13}	0	0	0.05	1	0
Sum	0.50	1	1.73	4.00	1.75
Rank	**1**	2	4	5	3

Table 9: Impact standardization from the MOGSA criteria F_{14} to F_{23}

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_{14}	0	0	0	0	1
F_{15}	0	1	0	0	0.14
F_{16}	0	0	0	0	0
F_{17}	0	0	0	0	0
F_{18}	0	0	0	0	0
F_{19}	0	0	0	0	0
F_{20}	0	0	0	0	1
F_{21}	0	0	0	0	1
F_{22}	0	0	0	0	1
F_{23}	0	0.00	0.00	0	1
Sum	0	1.00	0	0	5.14
Rank	1	4	2	3	**5**

Table 10: Impact standardization from the MOGSA criteria F_{14} to F_{23}

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_{14}	0	0.27	0.09	0	1
F_{15}	0	0.25	0.10	1	0.10
F_{16}	0	0	0	0	0
F_{17}	0	0	0	0	0
F_{18}	0	0	0	0	1
F_{19}	0	0	0	0	1
F_{20}	0.34	0	0.99	1	0.94
F_{21}	0	0.84	0.99	0.54	1
F_{22}	0.10	0	0.65	0.47	1
F_{23}	0.11	0	0.96	0.15	1
Sum	0.56	1.36	3.79	3.16	7.04
Rank	**1**	2	4	3	5

Table 11: Impact standardization from the MOGSA criteria F14 to F23

Function	MOG.S.A.	G.S.A.	B.A.T.	P.S.O.	G.A.
F_{14}	0	0.27	0.09	0	1
F_{15}	0	0.25	0.10	1	0.10
F_{16}	0	0	0	0	0
F_{17}	0	0	0	0	0
F_{18}	0	0	0	0	1
F_{19}	0	0	0	0	1
F_{20}	0.34	0.00	0.99	1.00	0.94
F_{21}	0	0.84	0.99	0.54	1
F_{22}	0.10	0	0.65	0.47	1
F_{23}	0.11	0	0.96	0.15	1
Sum	0.56	1.36	3.79	3.16	7.04
Rank	**1**	2	4	3	5

1.7 Overview of Al - Nnoaman Plastic Company:

Al-Nnoaman Plastic Co. was established in 1986 as an industrial plant specialized in the production of drip irrigation systems, fixed spray and its fittings from high polyethylene pipes, density wadding, piping connections, production of plastic houses, agricultural nylon, waste container, waste bags, Automatic, traditional and semi-programmed milling and metal springs production machines. Though the company started with only twenty-five billion shares, by the year 2010 this number grown to about one hundred billion shares. In that regards, the tremendous improvement recorded gave the company opportunity to establish factories and factories affiliated to the production of plastic of many kinds.

Figure 1: Al - Nnoaman Plastic Company

Figure 2 illustrate the different sizes and shapes of the production for the above company and custom measurements respectively.

Figure 2: High density polyethylene pipes (HDPE)

Table 12: HDPE (PE100) Dimensions of Tubing (ISO 4427)

Operating Pressure PE 63				**PN 2.5**				**PN 3.2**				**PN 4**				**PN 5**			
Operating Pressure PE 80				**PN 3.2**				**PN 4**				**PN 5**				**PN 6**			
Operating Pressure PE 100				**PN 4**				**PN 5**				**PN 6**				**PN8**			
Ratio of Normal Diameter (SDR)				**SDR 41**				**SDR 33**				**SDR 26**				**SDR 21**			
Nom Size mm	**Mean Outside Diameter**		**Modality**	**Wall thickness-t**		**Pipe ID and Weight**		**Wall thickness-t**		**Pipe ID & Weight**		**Wall thickness-t**		**Pipe ID and Weight**		**Wall thickness-t**		**Pipe ID and Weight**	
	Min.	**Max.**	**Max.**	**Min.**	**Max.**	**I.D**	**Kg/m**	**Min.**	**Max.**	**I.D**	**Kg/m**	**Min.**	**Max.**	**I.D**	**Kg/m**	**Min.**	**Max.**	**ID**	**Kg/m**
16	16	16.3	1.2																
20	20	20.3	1.2																
25	25	25.3	1.2																
32	32	32.3	1.3																
40	40	40.4	1.4													2	2.3	36	0.24
50	50	50.4	1.4									2	2.3	46	0.31	2.4	2.8	45	0.37
63	63	63.4	1.5									2.5	2.9	58	0.49	3.0	3.4	57	0.57
75	75	75.5	1.6									2.9	3.3	69	0.67	3.8	4.1	67	0.84
90	90	90.6	1.8									3.5	4.0	83	0.97	4.3	4.9	81	1.17
110	110	110.7	2.2									4.2	4.8	101	1.42	5.3	6.0	99	1.76
125	125	125.8	2.5									4.8	5.4	115	1.83	6.0	6.7	112	2.25

140	140	140.9	2.8									5.4	6.1	128	2.3	6.7	7.5	126	2.82
160	160	161	3.2									6.2	7	147	3.02	7.7	8.6	144	3.69
180	180	181.1	3.6									6.9	7.7	165	3.76	8.6	9.6	162	4.64
200	200	201.2	4									7.7	8.6	184	4.67	9.6	10.7	180	5.75
225	225	226.4	4.5									8.6	9.6	207	5.86	10.8	12	202	7.27
250	250	251.5	5									9.6	10.7	230	7.27	11.9	13.2	225	8.89
280	280	281.7	9.8									10.7	11.9	257	9.06	13.4	14.9	252	11.23
315	315	316.9	11.1	7.7	8.6	299	7.46	9.7	10.8	295	9.32	12.1	13.5	289	11.54	15.0	16.6	283	14.11
355	355	357.2	12.5	8.7	9.7	337	9.49	10.9	12.1	332	11.79	13.6	15.1	326	14.59	16.9	18.7	319	17.91
400	400	402.4	14	9.8	10.9	379	12.04	12.3	13.7	374	15.02	15.3	17	368	18.5	19.1	21.2	360	22.84
450	450	452.7	15.6	11.0	12.2	427	15.18	13.8	15.3	421	18.91	17.2	19.1	414	23.39	21.5	23.8	405	28.89
500	500	503	17.5	12.3	13.7	474	18.9	15.3	17	468	23.32	19.1	21.2	460	28.72	23.9	26.4	450	35.64
560	560	563.4	19.6	13.7	15.2	531	23.53	17.2	19.1	524	29.35	21.4	23.7	515	36.17	26.7	29.5	504	44.61
630	630	633.8	22.1	15.4	17.1	598	29.77	19.3	21.4	589	37.03	24.1	26.7	579	45.83	30.0	33.1	567	56.35

The table 12 illustrated the different size and dimension for High density polyethylene pipes and the table also includes four pipes in different for Standard Diameter Ratio. Details about these pipes that used in this work are shown in Table 13.

1.8 Problem Description of Al - Nnoaman Plastic Company:

Al-Nnoaman Plastic Co. is one of the most popular and large plastic Co. in Iraq. However, the important problem in this company was non-optimal planning of the quantities produced and stored as the company relies on the previous methods of production planning and scheduling problem which led to the lack of optimal utilization of available energies. Consequently, this company overwhelms over produce or under produce which is inconsistent with the actual demand, thus, resulting to rising costs and lower profits. The mathematical model used to solve this problem is presented deeply in the subsections (5.2.1 and 5.2.2).

1.8.1 Data Description:

According to the preliminary environmental information of Al-Nnoaman Plastic Company, Al-Nnoaman Plastic Company produces 55 types of product. Table 5.6 summarizes the related productions and introduce the details about the products are using in this work. Relevant data are as follows in the next section. In addition, all the details of the production planning can be observed in tables (5.6 and 5.7). Table (5.6) shows the products involved in the production planning, different sizes, normal processing time and crashing processing time, the rate of deterioration, the constant cost of each product, the cost of normal processing time and crashing processing time respectively and time available for the machine. Table 14 shows the demand for each product within six months for different size.

Table 13: Operating costs and data for all products

Size	Products	P_n	P_c	f_i	k	So	SCo	CSn	CSc	AT
0.5 in	Pipe /P 25B	140	93	0.265656	7010950	4	3400	875	1317	8880000
0.75 in	Pipe /P 25B	3	0.500	0.101682	8400405	4	3400	1800	1800	87840000
1 in	Pipe /P 10B	10	7	0.285106	9607800	4	3400	490	790	86880000
1.5	Pipe /P 10B	5	3	0.344652	9800694	4	3400	1000	1333	94560000
2 in	Pipe /P 10B	5	3	0.13226	8269902	4	3400	1580	1840	90720000
3 in	Pipe /P 10B	5	3	0.217066	6416973	4	3400	2370	2370	89280000

Table 14: Predicted demand (d)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	700000	700000	700000	700000	700000	700000
0.75 in	Pipe /P 25B	500	500	500	500	500	500
1 in	Pipe /P 10B	10000	10000	10000	10000	10000	10000
1.5	Pipe /P 10B	7500	7500	7500	7500	7500	7500
2 in	Pipe /P 10B	5000	5000	5000	5000	5000	5000
3 in	Pipe /P 10B	3000	3000	3000	3000	3000	3000

And the Table 15 presents the results

Table (15): Setup cost for all product on machine (SC)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	0	35500	35100	34000	35000	35000
0.75 in	Pipe /P 25B	33000	0	33000	33300	34000	33000
1 in	Pipe /P 10B	34500	33500	0	33500	32500	34000
1.5	Pipe /P 10B	35600	34000	34000	0	33000	35500
2 in	Pipe /P 10B	35000	35000	34000	32000	0	32500
3 in	Pipe /P 10B	36000	33000	32000	33500	32500	0

Table (16): Unit inventory holding cost (h)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	1	1	1	1	1	1
0.75 in	Pipe /P 25B	5	5	5	5	5	5
1 in	Pipe /P 10B	1	1	1	1	1	1
1.5	Pipe /P 10B	2	2	2	2	2	2
2 in	Pipe /P 10B	2	2	2	2	2	2

3 in	Pipe /P 10B	3	3	3	3	3	3

Table (17): Unit deterioration cost (Pai)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	875	875	875	875	875	875
0.75 in	Pipe /P 25B	1800	1800	1800	1800	1800	1800
1 in	Pipe /P 10B	490	490	490	490	490	490
1.5	Pipe /P 10B	1000	1000	1000	1000	1000	1000
2 in	Pipe /P 10B	1580	1580	1580	1580	1580	1580
3 in	Pipe /P 10B	2370	2370	2370	2370	2370	2370

1.8.2 MCDM Theories:

Several hypotheses or Multi-criteria decision-making methods have been studied.. Multiplication of exponential weights (MEW, WPM), Weighted-Sum Models, Basic Additive weighting, HAW, Atrial Natriuretic Peptide (ANP), and TOPSIS are the most common approach to MADM using different concepts;[9] [10]. As far as we are aware, no tool was used to calculate digital watermarking approaches.The advantages, disadvantages, and guidelines of common MCDM approaches can be summed up as follows, according to literature [11]; [12]; [13]; [14]; and [16«. WSM and HAW are simple to utilize and see, however boundary loads are subjective; the two methodologies are hard to use with an expanding measure of details. (target work). Another significant hindrance to these techniques is the utilization of basic mathematical scaling to get the last positioning. SAW considers all boundaries (target function), takes intuitive judgments, and makes a straightforward calculation; but the maximum and positive values of the criteria (objective function) are all to be found.Furthermore, the present state is not always expressed in SAW. The qualities of MEW and WPM are to eliminate any estimation unit and to utilize relative as opposed to genuine qualities. No arrangement is, nonetheless, given to frameworks with equivalent choice weight. TOPSIS is practically identified with discrete substitute subjects. In reality, this is perhaps the most useful techniques for tackling issues. TOPSIS has an overall advantage of having the option to locate the best arrangement without any problem. Instead, TOPSIS's key drawback is the lack of weight-raising allowance and consistent clarification of decisions.The human ability for information retrieval greatly restricts the use of ANP; 7 ± 2 is also used as a reference ceiling[17]. TOPSIS reduces the requisite paired comparisons from that point of view and the capacity limit does not significantly dominate the operation. TOPSIS is also ideal for situations with multiple characteristics and alternatives. Where analytical or measurable statistics are given, the approach is particularly handy to use. For these reasons, TOPSIS was used to address certain real-world challenges. The fuzzy approach helps decision-makers to use verbal language to assess decisions and facilitate decision-making by taking into account vagueness and ambiguity of human decision-making. For both options, though, the calculation of the fluffy reasonableness record and positioning qualities is troublesome. The open elective scores have been positioned in a diminishing request and the inclination for the most unexploited arrangements is TOPSIS. Just a peek into the urgency of non-dominated alternatives provides detailed scores. As with other ranking decisions, people can also rely on the most urgent alternatives. Based on their geometrical distance from the positive and negative, TOPSIS allocates the scores for every other option (per non-ruled arrangement). The MOGSA elective was chosen by you. As depicted in the means beneath, the MOGSA will have the briefest mathematical distance to the positive ideal arrangement and the longest mathematical separation from the negative ideal.

Step 1: Development of the customary choice network

This move changes over various dimensional ascribes into non-dimensional credits for credits examination. From that point on, the lattice$(x_{ij})_{m*n}$is normalized on $(x_{ij})_{m*n}$ to the matrix $R = (r_{ij})_{m*n}$ al-(m*n) utilizing the normalization method.

$$r_{ij} = x_{ij} \Big/ \sqrt{\sum_{i=1}^{m} x_{ij}^2} \text{ for all } i = 1, \dots, m \text{ and } j = 1, \dots, n \qquad (1)$$

A new matrix R, shown below, is the result of this step.

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \qquad (2)$$

Step 2: Structured Weighted choice framework development

A collection of weights is used in the normalized decision-making matrix: W=w1,w2,w3,..., wj,...,wn where a choice framework j = 1,...,n. Multiplying each column with its equivalent weight defines the resulting matrix. wj from the regular decision matrix R. The weight set is equivalent to 1.

$$\sum_{j=1}^{m} w_j = 1 \qquad (3)$$

The product of this step is a new V matrix, as seen below.

$$V=\begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix}=\begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \quad (4)$$

Step 3: Assurance of The ideal and negative ideal other options

Two artificial alternatives to this move (non-dominated solutions)A^* (The best substitute) and A^-(The option in contrast to the negative ideal) is known as

$$A^* = \left\{\left(\left(\max_i \ v_{ij} \middle| j \in J\right), \left(\min_i v_{ij} \middle| j \in J^-\right) \middle| \quad i = 1,2, \dots, m\right)\right\}$$

$$= \{v_1^*, v_2^*, \dots, v_j^*, \cdots v_n^*\}(5)$$

$$A^- = \left\{\left(\left(\min_i \ v_{ij} \middle| j \in J\right), \left(\max_i v_{ij} \middle| j \in J^-\right) \middle| i = 1,2, \dots \dots \dots, m\right)\right\}$$

$$= \{v_1^-, v_2^-, \dots, v_j^-, \cdots v_n^-\}(6)$$

When J is a sub-set of { i=1,2,...,m} that displays the advantage characteristic (i.e., Providing an expanding utility with its higher features), and J^-Is J's supplement kit. You can also apply the other thing to the cost attribute shown by J^c.

Step 4: Euclidean distance separation estimation.

The separation calculation is carried out in this progression by estimating the distance between every other option (non-overwhelmed arrangement) in V and the ideal A^*Vector that uses the distance Euclidean given by the distance Euclidean.

$$S_{i^*} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^*\right)^2}, \qquad i = \{1,2, \dots \dots m\}, \qquad (7)$$

In like manner, the count of division for every other option (non-ruled arrangement) in V from the negative idealA^- is given by the negative idealA^- .

$$S_{i^-} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}, \qquad i = \{1,2, \dots \dots m\}, \qquad (8)$$

Two numbers, respectively, S(i) and S(i-), are counted at the end of step 4 for each alternative. The distance between and elective and both the ideal and the negative ideal is communicated by these two qualities.

Step 5: Closeness of estimating the optimal solution

The closeness of $A_i$to the ideal arrangement $A^*$is characterized in this progression as:

$$C_{i^*} = S_{i^-}/(S_{i^-} + S_{i^*}), \quad 0 < C_i \quad < 1, \qquad i = \{1,2, \ldots \ldots m\}, \qquad (9)$$

Clearly, $C_{i^*} = 1$if and just if $A_i = A^*$Additionally, $C_{i^*} = 0$if and just if $A_i = A^-$.

Step 6: Classification of the alternative by the nearness to the ideal arrangement.

The set of equivalents (A_i) is now ranked in the descending order of (C_{i^*}); the highest value reflects the effectiveness of the MOGSA.

1.8.3 Results and Findings for the Applications:

A comparatively complicated topic with a growing number of constraints and decision variables is the multi-objective multi-product preparation challenge and scheduling problem. An NP-hard problem is the easiest problem with a single cost goal. In Table 13, a new solution method for solving the Al-Nnoaman Plastic Business problem involving the results is presented. If a set-up period for and commodity is provided in Table 13 within six months. Data output from output

Table (18): Production (P)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	692557.98	694187.35	694191.91	765917.71	739081.51	731603.71
0.75 in	Pipe /P 25B	495.52	496.54	496.43	547.57	528.32	522.91
1 in	Pipe /P 10B	9894.51	9917.65	9917.60	10942.16	10558.70	10451.81
1.5	Pipe /P 10B	7421.09	7438.41	7438.34	8206.74	7919.13	7838.94
2 in	Pipe /P 10B	4947.67	4959.17	4959.09	5471.32	5279.55	5226.07
3 in	Pipe /P 10B	2968.94	2975.78	2975.68	3282.98	3167.89	3135.78

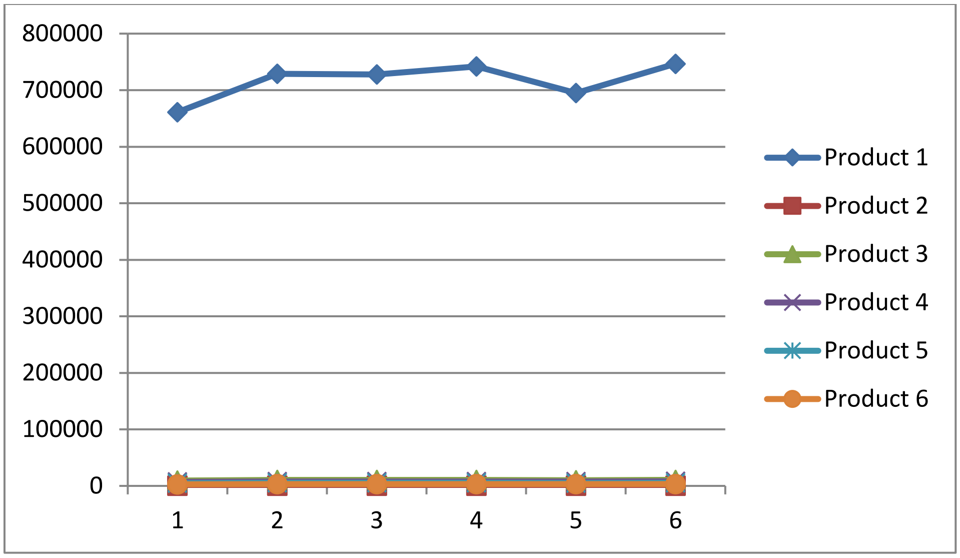

Figure (3): Chart area of production

Table (19): Inventory (I)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	0	0	17912.42	54849.61	35449.38	72701.39
0.75 in	Pipe /P 25B	0	0	14.89956	43.64912	36.16302	66.15581
1 in	Pipe /P 10B	0	0	257.9681	780.5485	489.4184	1016.917
1.5	Pipe /P 10B	0	0	194.0027	574.3563	325.0605	713.3878
2 in	Pipe /P 10B	0	0	130.0373	411.144	322.6715	613.68
3 in	Pipe /P 10B	0	0	78.86498	240.9222	168.3302	332.1364

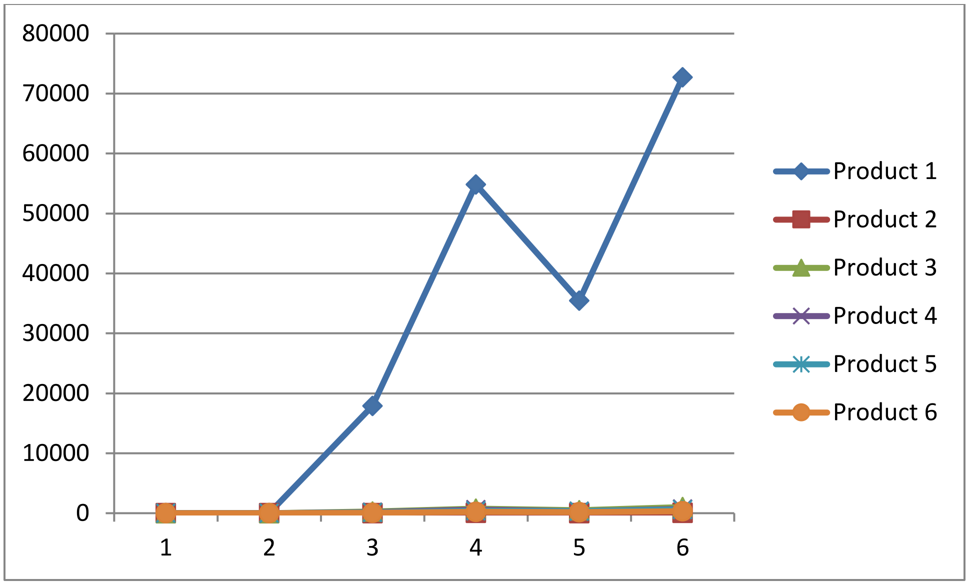

Figure (5.10): Chart area of inventory

Table (20): Backorder (B)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	38874.2	10033.38	0	0	0	0
0.75 in	Pipe /P 25B	26.93455	5.640013	0	0	0	0
1 in	Pipe /P 10B	554.5243	141.828	0	0	0	0
1.5	Pipe /P 10B	415.6849	105.9891	0	0	0	0
2 in	Pipe /P 10B	276.8455	70.15013	0	0	0	0
3 in	Pipe /P 10B	165.7739	41.47897	0	0	0	0

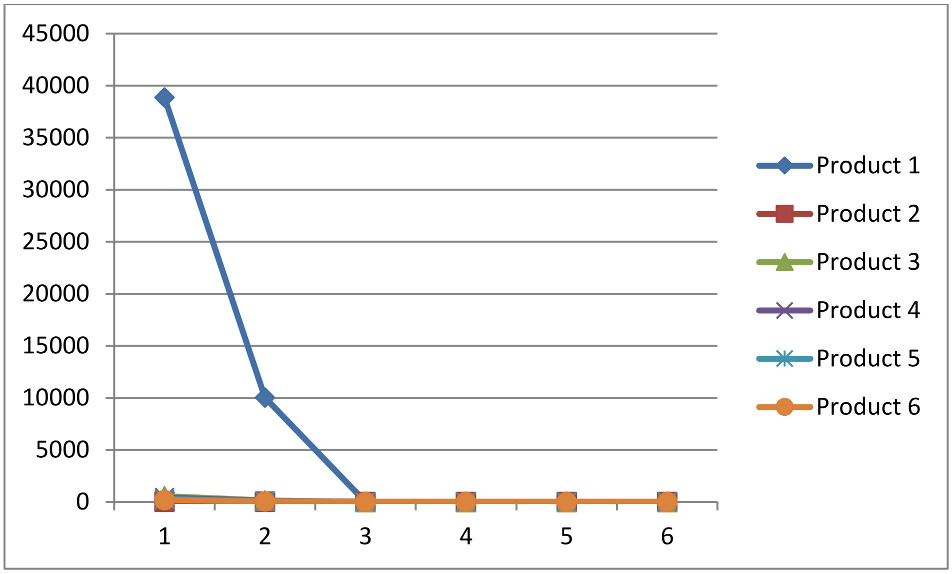

Figure (5): Chart area of backorder

Table (21): Scheduling (SCh)

Size	Products	Jan	Feb	Mar	Apr	May	Jun
0.5 in	Pipe /P 25B	0	0	0	0	0	1
0.75 in	Pipe /P 25B	0	0	0	0	0	0
1 in	Pipe /P 10B	0	1	0	0	0	0
1.5	Pipe /P 10B	0	0	1	0	0	0
2 in	Pipe /P 10B	1	0	0	0	0	0
3 in	Pipe /P 10B	0	0	0	1	0	0

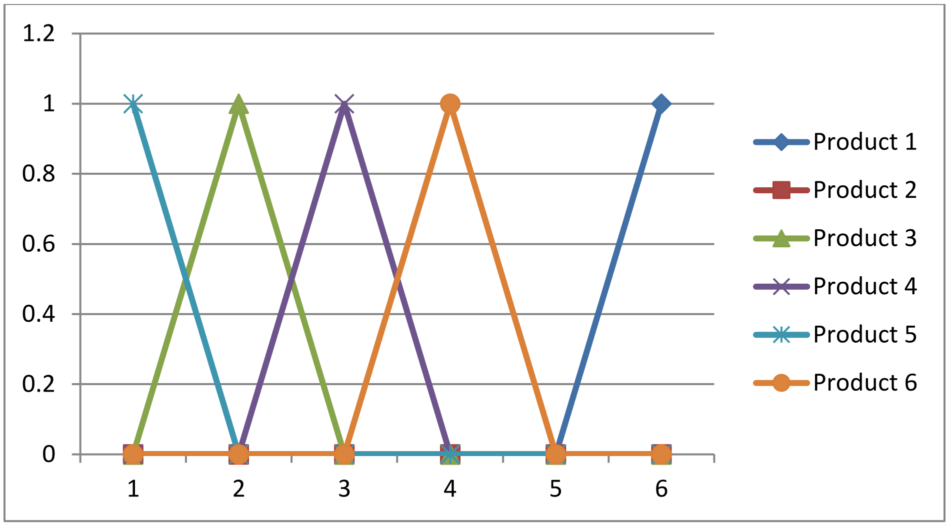

Figure (6): Chart area scheduling

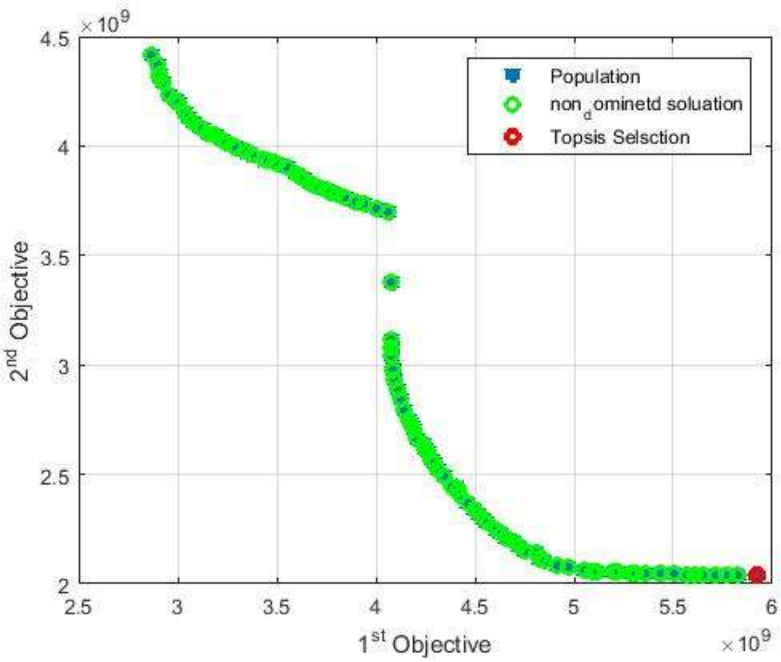

Figure (7): Chart area scheduling

1.9 Discussion:

From the Table 2, the criteria MOGSA means the lowest value obtained by the function during the process of repetition. What's more, the mean, implies that the normal worth got by the capacity during the cycle of reiteration. The most noticeably awful standards imply that it is the most noteworthy worth acquired by the cycle during the cycle of reiteration. At last, the Std. this implies that these qualities are a long way from the qualities in the focuses.

For all the capacities in Table 1, regarding productivity, MOGSA gives preferable outcomes over GSA, BAT, PSO, and GA. In any case, for the unimodal capacities, the best dissimilarity between the calculations exists.

Table 2 uncovers that, with all the boundaries, MOGSA displays MOGSA impacts in F1, F2, F3, F4, and F7. For the MOGSA boundary and the MOGSA for all the boundaries in F6, PSO is simpler in F5. For the middle standard, MOGSA is better, yet terrible for the Std. Basis in F5. By utilizing the accompanying condition as proposed by Jain and Bhandare (2011), the scientist standardizes calculations and capacities:

$$\text{Normalization} = \frac{f_i - \text{best}}{\text{worst} - \text{best}} \qquad (2)$$

Where f_i addresses the estimation of target work for condition, best is the populace, the MOGSA arrangement, and the most noticeably awful indicates the most exceedingly terrible in the populace arrangement. The last lines of the sections (3, 4, and 5) in the calculation positioning. The most recent examination applies the condition (2) to tables (3-5).

Tables (3-5) show every calculation's positioning (sections) regarding F-1 to F-77 (lines). With GSA, BAT, PSO and GA, Table 3 shows the MOGSA rules of MOGSA from F-1 to F-7. The mean rules for the cream figuring in the seven components of GSA, BAT, GA and PSO is given in Table 4. Accordingly, the most noticeably terrible basis for the half and half calculation from F 1 to F 7 with GSA, BAT, GA, and PSO can be noticed Table 5. It recommends the speed of the mixing speed correlated with the figures.The PSO results are higher for the MOGSA guidelines than those for MOGSA in F5. The inspector includes the usage in GSA, BAT, and GA of the MOGSA rules and the inimitable nature of the MOGSA figuring in F5. The results gained using the hybrid estimation's mean premise, regardless, show a bigger number of focal points than those of the large number of various counts. MOGSA in this manner considers enlivened gathering for all test benchmark feature cases relative with various figuring's in F6 and F7 Table 3. Also, the get together rate contrasts differentiated and those of the other algorithmic limits when the most observably horrible principle is used in all the results. The enthralling power of MOGSA is credited to mixing.

In this way, a solid MOGSA union rate can be surmised. The worldwide ideal will in general be arrived at quicker by MOGSA than different calculations. MOGSA, be that as it may, has a more significant level of intermingling than different calculations.

Multimodal high-dimensional capacities: There are a few neighbourhood minima in multimodal capacities, which are hard to enhance. In the wake of finding a close worldwide ideal and feeble neighbourhood optima, they address the limit of a calculation to get away. The ultimate results are significant.

The current exploration performs probes F8 to F 13, in which the quantity of nearby minima increments dramatically as the component of the capacities increments. The extents are diverse for these capacities. 20 runs are the average cycle of the outcomes.

Low-dimensional multimodal capacities: For the low-dimensional multimodal benchmark concerns presented in Tables 2 and 6, which compare MOGSA, GSA, GA, BAT, and PSO. The revelations exhibit that these estimations have similar plans and that they show exactly the same results.

Table 6 uncovers that MOGSA for the MOGSA standard is best in F-8, PSO for the mean and most extremely terrible limits is better in F8, and GA for the Std. is better in F8. Benchmark. For all the limits in F9 and F 12, MOGSA is higher. In F10, for the MOGSA standard, MOGSA is ideal, while PSO is better for the mean, most recognizably horrendous and Std. Requirements. In the end, PSO is better for the mean, most incredibly terrible and Std. in F-11, yet GA is better for the MOGSA norms and in F_13 GA is superior to the others for the mean, most incredibly awful, and Std. rules.

Tables (7-9) show the situating that identifies with F8 to F13 for each computation (areas) (segments). In F-8 to F-13 with GSA, BAT, GA, and PSO Table 3, the MOGSA essential of the creamer count is refined.

The mean measure of MOGSA in seven capacities with the over four calculations is appeared in Table 8. Nonetheless, Table 9 uncovers that the most exceedingly awful of the MOGSA boundaries occurred somewhere in the range of F8 and F13. The intermingling speed rate is associated with the calculations. Capacities (lines) rely upon the standards for MOGSA. The crossover (section) calculations are stood out from the other Table 8 calculations. Practically all occasions of checking the MOGSA rules are best in F8 and F13 for the proposed calculations, Compared to MOGSA in F9, F10, and F11, the GSA results are higher for the MOGSA model. At last, utilizing GA in F12, more grounded results can be accomplished.

The investigations that utilized the mean MOGSA rule in F-8 and F13, notwithstanding, had more advantages comparative with those that utilized different boundaries. GSA, PSO, and GA show great outcomes in F9,F10, F11 and F12, individually, for similar measures. In correlation, the positioning of the crossover calculation in F8 and F13 is better than that of the others when the most exceedingly terrible boundary is utilized. GSA, PSO, and GA show great outcomes in F9, F11, F10 and F12, separately, under similar standards. Because of the engaging force of MOGSA, the union pace of MOGSA is diverged from that of the other calculation. The solid pace of union of MOGSA can, nonetheless, be surmised. MOGSA will in general be less difficult than different calculations to arrive at the worldwide ideal, and along these lines has a preferred combination rate over different calculations..

The calculations are recognized by MOGSA in Table 10. The two calculations in F16,F17,F18,and F19 have a similar MOGSA, mean, and most exceedingly terrible boundaries, except for GA, which has separate qualities for the mean and most exceedingly awful standards in F18 and F19. In F16 and F19, the GSA esteem for the Std. is better. Benchmark. In F17 and F18, BAT has the MOGSA esteem for the Std. Benchmark.

The MOGSA for the Std. BAT calculation executes the F14 models. The two calculations show similar proficiency in the MOGSA rules, aside from GA, in a similar capacity too. MOGSA and PSO get better outcomes in F14 in the mean and most noticeably terrible boundaries, and BAT and PSO calculations have similar qualities, which are superior to those of the others for the MOGSA rule, and MOGSA accomplishes the mean and most exceedingly terrible basis MOGSA score. In the in the interim, GA has the estimation of MOGSA in Std. Benchmark. In F20, for the MOGSA model, MOGSA, GSA, and PSO have similar qualities, and BAT is better for the mean boundaries. In a similar capacity, GSA is the MOGSA for the mean, most exceedingly terrible and Std. Necessities. The two calculations have similar qualities for the MOGSA standards in F21, F22, and F23, aside from GA, which has huge and unmistakable qualities for similar capacities. MOGSA executes the MOGSA in F21 for different boundaries, and. The MOGSA commitment for the mean, most noticeably terrible, and Std. is seen in F23 by GSA. Necessities.

The positioning of every calculation (sections) relating to F14 to F23 is appeared in tables (11-13). (lines). For F14 to F23, the MOGSA standards for MOGSA is equivalent to for GSA, BAT, GA, and PSO Table 11. The mean crossover calculation standards for seven capacities, alongside those for GSA, BAT, GA, and PSO, is appeared in Table 12. The most noticeably awful standard for MOGSA, however, shows up in Table 13 from F14 to F23.

The pace of union corresponding to the calculation is characterized as follows. MOGSA, GSA, BAT, and PSO are better than different calculations in both F14 and F21. The discoveries of all the knowledge calculations are higher in F16,F17,F18,F19,and F23 than those of different calculations. BAT does higher at F20 than the others in Table 2. The MOGSA effectiveness is shown by GA in F15 and F22. Moreover, in F16, F17, and F23 Table 12, all the calculations reliant on the mean rule have negative boundlessness esteems and we place negative endlessness esteems equivalent to nothing. For GA in F18, F19, and F22, in any case, the worth is equivalent to nothing. In F14 and F21, BAT is better, while in F20, MOGSA is better for all the outcomes. Contrasted with different calculations, of MOGSA the result shows the alluring power MOGSA.

The strong rate of convergence of MOGSA can, however, be inferred. In this way, MOGSA winds up arriving at the worldwide ideal speedier and with a higher union rate than different calculations.

1.10 Conclusion:

This theory proposes MOGSA, another enhancement plot dependent on the GSA gravity law and the BAT bats' echolocation conduct. Actualizing MOGSA as an enhancement calculation may have significant advantages from the strength and coordination of the two calculations. To survey its yield, this examination actualizes MOGSA on a bunch of 23 standard test capacities. Much of the time, the outcomes got by MOGSA are predominant and, in all cases, equivalent to the consequences of PSO, GA, GSA, and BAT. At last, on the two calculations, the scientist conducts standardization and the outcome shows MOGSA's predominance.

As can be construed from the above conversation, MOGSA crossover calculations were presented and depicted in this section. What's more, another MOGSA mixture calculation is proposed to be created to support the Swarm Intelligence SI area. What's more, these new crossover calculations are appeared differently in relation to other people.

References:

[1] Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2009). GSA: a gravitational search algorithm. Information Sciences, 179(13), 2232-2248.

[2] Yang, X.-S. (2010). A new metaheuristic bat-inspired algorithm. Nature inspired Cooperative strategies for optimization (NICSO 2010), 65-74.

[3] Ellabib, I., Calamai, P., & Basir, O. (2007). Exchange strategies for multiple ant colony system. Information Sciences, 177(5), 1248-1264.

[4] Tarasewich, P., & McMullen, P. R. (2002). Swarm intelligence: power in numbers. Communications of the ACM, 45(8), 62-67.

[5] Eberhart, R., & Kennedy, J. (1995). A new optimizer using particle swarm theory. Paper presented at the Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on.

[6] Tang, K.-S., Man, K.-F., Kwong, S., & He, Q. (1996). Genetic algorithms and their applications. IEEE signal processing magazine, 13(6), 22-37.

[7] Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. IEEE transactions on evolutionary computation, 1(1), 67-82.

[8] Zanakis, Stelios H., et al. "Multi-attribute decision making: A simulation comparison of select methods." European journal of operational research 107.3 (1998): 507-529.

[9] Zaidan, A. A., et al. "Evaluation and selection of open-source EMR software packages based on integrated AHP and TOPSIS." Journal of biomedical informatics 53 (2015): 390-404.

[10] Zaidan, A. A., et al. "Multi-criteria analysis for OS-EMR software selection problem: A comparative study." Decision support systems 78 (2015): 15-27.

[11] Yoon, K. Paul, and Ching-Lai Hwang. Multiple attribute decision making: an introduction. Vol. 104. Sage publications, 1995.

[12] Mollaghasemi, Mansooreh, and Julia Pet-Edwards. "Making multi-objective decisions." Institute of Electrical & Electronics Engineering (1997).

[13] Triantaphyllou, Evangelos, et al. "Multi-criteria decision making: an operations research approach." Encyclopedia of electrical and electronics engineering 15.1998 (1998): 175-186.

[14] Triantaphyllou, Evangelos. "Multi-criteria decision making methods." Multi-criteria decision making methods: A comparative study. Springer, Boston, MA, 2000. 5-21.

[15] Aruldoss, Martin, T. Miranda Lakshmi, and V. Prasanna Venkatesan. "A survey on multi criteria decision making methods and its applications." American Journal of Information Systems 1.1 (2013): 31-43.

[16] Yas, Qahtan M., et al. "Towards on develop a framework for the evaluation and benchmarking of skin detectors based on artificial intelligent models using multi-criteria decision-making techniques." International Journal of Pattern Recognition and Artificial Intelligence 31.03 (2017): 1759002.

[17] Saaty, Thomas L., and Mujgan Ozdemir. "Negative priorities in the analytic hierarchy process." Mathematical and Computer Modelling 37.9-10 (2003): 1063-1075.