Application and Development of Enhanced Chaotic Grasshopper Optimization Algorithms

Akash Saxena (Ph.D.)

Presentation Flow

- An overview to new class of Algorithms (Chaotic-Algorithms)
- Types of Chaotic Algorithms
- An overview of Chaotic GOA Project
- Overview of Grasshopper Optimisation Algorithm
- Development and Application of Enhanced Chaotic Grasshopper Optimization Algorithms
- Studies and Test Cases

Chaos Breeds Life While Order Breeds Habit

The world is such a busy place, it's chaotic.

Chaos

- Chaos is **indeterminism** at its best — a concept totally foreign and unwelcome in Laplace's world. The scientific usage of the word was first coined by Yorke and Li in their ground breaking paper, "Period Three Implies Chaos (1975)," in which they described particular flows as chaotic.

In short, chaos embodies three important principles:

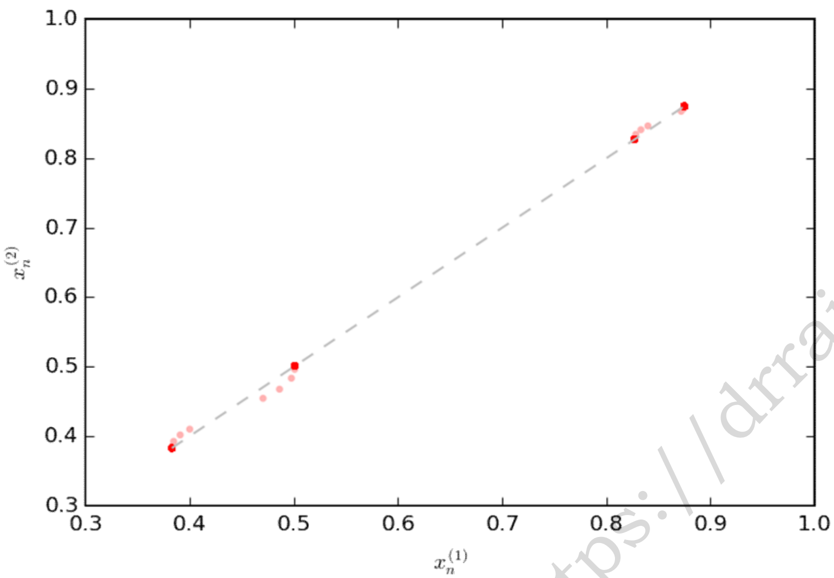
- **Extreme** sensitivity to initial conditions
- Cause and effect are **not** proportional
- Nonlinearity

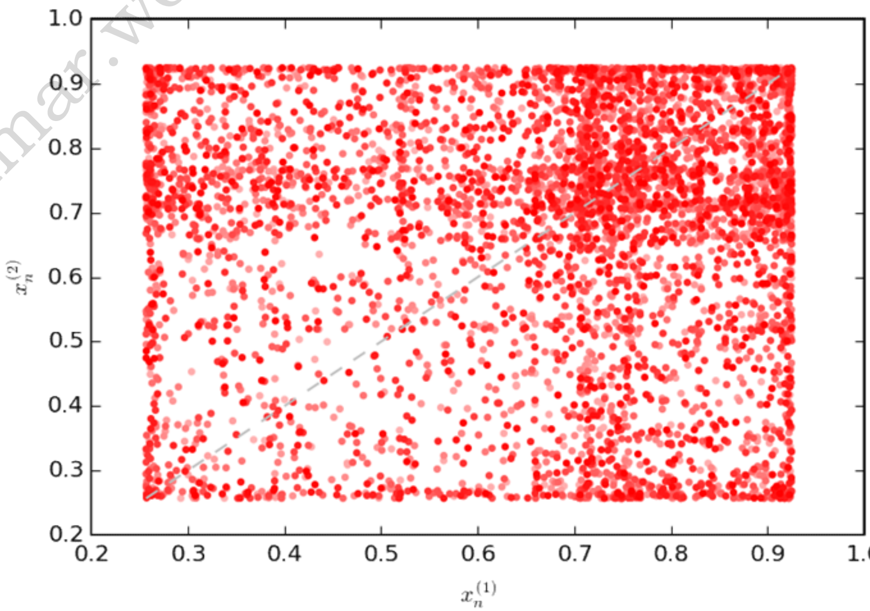
Chaos v/s Random

- It is important to not confuse randomness with unpredictability. Random behavior is not predictable in a strict sense (one can't make *perfect* predictions), but it can be predictable to a high degree of accuracy.
- Conversely, unpredictability can be due to randomness (like the inability to predict exactly when a radioactive decay will take place), but in most cases it's simply due to our inability to measure the initial state of a system accurately enough and follow it through accurately enough.
- Story of "Butterfly effect" –Sir Edward Lorentz.

Example of Chaotic Behavior (Logistic map)

$$x_{n+1} = r x_n \left(1 - x_n\right) \qquad For\ x_n = 0.4\ \&\ 0.41\ r = 3.5\ and\ 3.7$$





Chaotic Algorithms

- In recent years, the trend of embedding chaos in the optimization algorithms has grown multifold. Usually, the chaotic algorithms employ chaotic sequences instead of random numbers, in the exploration phase or they employ chaotic numbers for decision making in the exploitation phase. In literature, the positive impact of chaos over the performance of algorithms have been studied and reported
- These Algorithms are subdivided into three categories:
- The algorithms which employ chaotic swarming.
- The algorithms which employ chaotic decision operators.
- The algorithms which employ chaotic bridging.

Chaotic Swarming

- Generation of chaotic population instead of random generation at the beginning phase of the algorithm have been used in many chaotic variants. Chaos Embedded Particle Swarm Optimization Algorithms (CEPSOAs) were proposed by Alatas et al. (2009).
- Chaotic numbers were employed to create colony for bee.
- A Uniform big bang-chaotic big crunch optimization based on uniform population method was proposed by Alatas (2011).

Alatas, B., Akin, E., & Ozer, A. B. (2009). Chaos embedded particle swarm optimization algorithms. Chaos, Solitons & Fractals, 40 , 1715-1734.

Alatas, B. (2010). Chaotic bee colony algorithms for global numerical optimization. Expert Systems wit Applications, 37 ,5682-5687.

Alatas, B. (2011). Uniform big bang-chaotic big crunch optimization. Communications in Nonlinear Science and Numerical Simulation, 16 , 3696-3703.

Chaotic Operators

- The behavior of operators like, crossover, mutation and other deciding operators of the developed variants have strongly influenced by the chaotic sequence (Caponetto et al.,2003). These variants are different from the originals because their working mechanisms are guided by chaotic numbers instead of any random number.
- Hence, the decision, whether the crossover, mutation and any other operation will be executed or not is decided by chaotic numbers.

Caponetto, R., Fortuna, L., Fazzino, S., & Xibilia, M. G. (2003). Chaotic sequences to improve the performance of evolutionary algorithms. IEEE transactions on evolutionary computation, 7 , 289-304.

Gandomi, A., Yang, X.-S., Talatahari, S., & Alavi, A. (2013a). Firey algorithm with chaos. Communications in Nonlinear Science and Numerical Simulation, 18 , 89-98.

Chaotic Bridging

- Recently, the work on chaotic bridging mechanism has been reported for Gravitational Search Algorithm (GSA) (Mirjalili & Gandomi, 2017). In this work the authors presented different chaotic gravitational constants for GSA.
- Project on Chaotic Bridging R. Kumar et al.

Mirjalili, S., & Gandomi, A. H. (2017). Chaotic gravitational constants for the gravitational search algorithm. Applied Soft Computing, 53 , 407-419.

Grasshopper Optimisation Algorithm

- Grasshoppers as herbivores cause severe damage to corps. The swarming behaviour of grasshopper depends on both nymph and adults. Nymph moves on rolling on the ground and feed on succulents and soft plants. An adult grasshopper can jump high in search of food and therefore have a larger area to explore.
- As a result, both types of movements are observed i.e. slow movement and abrupt movement of large range which represents exploration and exploitation. The Grasshopper swarms are consist of three factors: Social Interaction, Gravitational forces and Wind advection.

$$X_i = S_i + G_i + A_i$$

$$S_i = \sum_{j=1,\ j \neq i}^{N} s\left(d_{ij}\right) \hat{d}_{ij} \qquad s(r) = fe^{-r/l} - e^{r} \qquad G_i = -g\hat{e}_g \qquad A_i = u\hat{e}_w$$

Position Update Equations

$$X_i = \sum_{j=1,\, j\neq i}^{N} s\left(\left|x_j - x_i\right|\right)\frac{x_j - x_i}{d_{ij}} - g\hat{e}_g + u\,\hat{e}_w$$

$$X_i^d = c\left(\sum_{j=1,\, j\neq i}^{N} c\,\frac{ub_d - lb_d}{2}\, s\left(\left|x_j^d - x_i^d\right|\right)\frac{x_j - x_i}{d_{ij}}\right) + \hat{T}_d$$

$$c = c_{\max} - l\left(\frac{c_{\max} - c_{\min}}{L}\right)$$

Effect of Parameter ‘c’

- In GOA, the parameter acts as a bridging mechanism for the exploration and exploitation phase over the whole course of iterations. In initial phase, the search agents take large steps to explore the search space in effective manner and in later case these steps are reduced with the help of linear decrement in the parameter c.
- The parameter c variation reduces the comfort zone, attraction and repulsion zone of the search agents. In a way, it controls the exploration phase by reducing these zones in later stages of iterative process.

Enhanced Chaotic Grasshopper Optimization Algorithms (R. Kumar et al.)

- Parameter c is an important parameter of GOA and used twice in position update equations of GOA the inner ‘c’ contributes to shrink the attraction and repulsion zone between grasshoppers.
- This effect is an analogous to the exploitation phase mechanism. However, with the increment in iteration counter outer ‘c’ reduces the search and help algorithm to converge.
- The comfort of grasshoppers is reduced with every iteration by varying the parameter c from 1 to zero linearly. However, in the proposed ECGOAs, chaotic sequence changes the boundary of comfort zone randomly in monotonically decreasing trend.
- This mechanism assists the search agents to release themselves from local minima trap. The transition from diversification phase to intensification phase can be achieved slowly with the employment of different chaotic sequences enabled adaptive approach. This change makes parameter c adaptive and random concurrently.

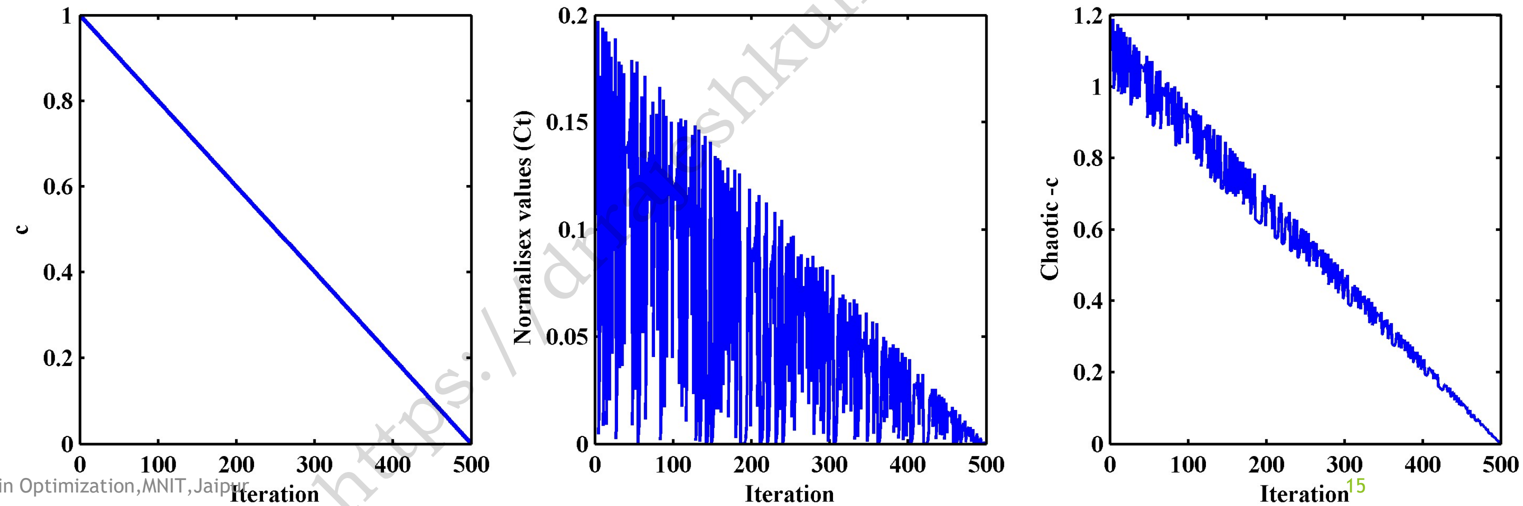
Saxena, A., Shekhawat, S., & Kumar, R. (2018a). Application and development of enhanced chaotic grasshopper optimization algorithms. Modelling and Simulation in Engineering, 2018 .

Evolution of Chaotic-C

$$N_m(l) = N_m^{\max} - \left(\frac{N_m^{\max} - N_m^{\min}}{L} \right) l$$

$$C(l) = N_m(l)\, x_l$$

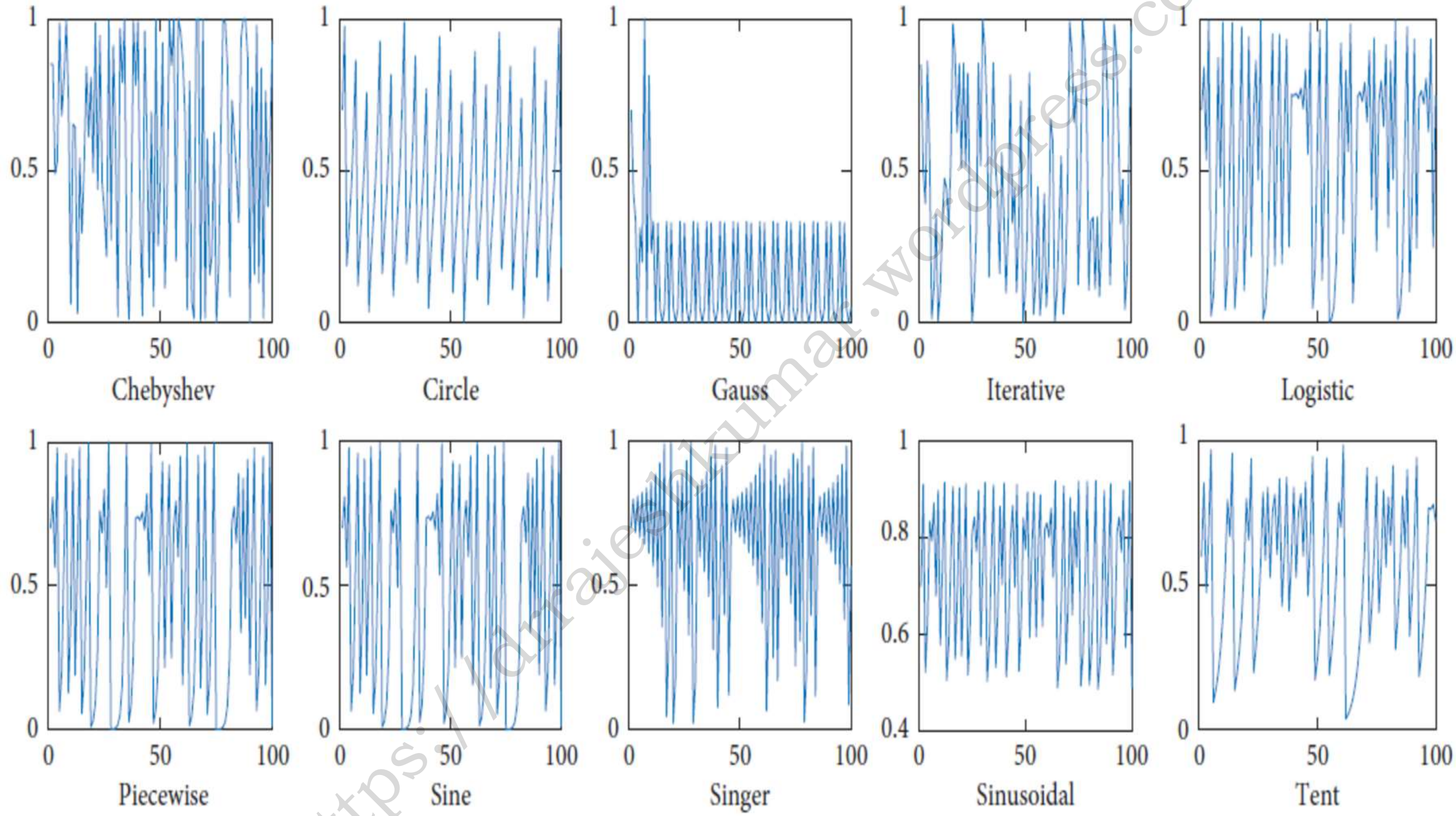
$$c^{ECGOA}(l) = c^{GOA}(l) + C(l)$$



Definition of Chaotic Maps

Name of map	Equation	Range
Chebyshev	$x_{k+1} = \cos(k \cos^{-1}(x_k))$	$(-1, 1)$
Circle	$x_{k+1} = \mathrm{mod}\{x_k + b - (a/2\pi)\sin(2\pi x_k, 1)\}, \quad a = 0.5,\ b = 0.2$	$(0, 1)$
Gauss	$x_{k+1} = \begin{cases} 1, & \text{if } x_k = 0 \\ (1/\mathrm{mod}(x_k, 1)), & \text{otherwise} \end{cases}$	$(0, 1)$
Iterative	$x_{k+1} = \sin(a\pi/x_k), \quad a = 0.7\ (\pi \approx 3.14)$	$(-1, 1)$
Logistic	$x_{k+1} = ax_k(1 - x_k), \quad a = 4$	$(0, 1)$
Piecewise	$x_{k+1} = \begin{cases} (x_k/P), & 0 \le x_k < P \\ ((x_k - P)/(0.5 - P)), & P \le x_k < 0.5 \\ ((1 - P - x_k)/(0.5 - P)), & 0.5 \le x_k \le 1 - P \\ ((1 - x_k)/P), & 1 - P \le x_k < 1 \end{cases} \quad P = 0.4$	$(0, 1)$
Sine	$x_{k+1} = (a/4)\sin(\pi x_k), \quad a = 4$	$(0, 1)$
Singer	$x_{k+1} = \mu(7.86x_k - 23.31x_k^2 + 28.75x_k^3 - 13.302875x_k^4), \quad \mu = 2.3$	$(0, 1)$
Sinusoidal	$x_{k+1} = ax_k^2 \sin(\pi x_k), \quad a = 2.3$	$(0, 1)$
Tent	$x_{k+1} = \begin{cases} (x_k/0.7), & x_k < 0.7 \\ (10/3)(1 - x_k), & x_k \ge 0.7 \end{cases}$	$(0, 1)$

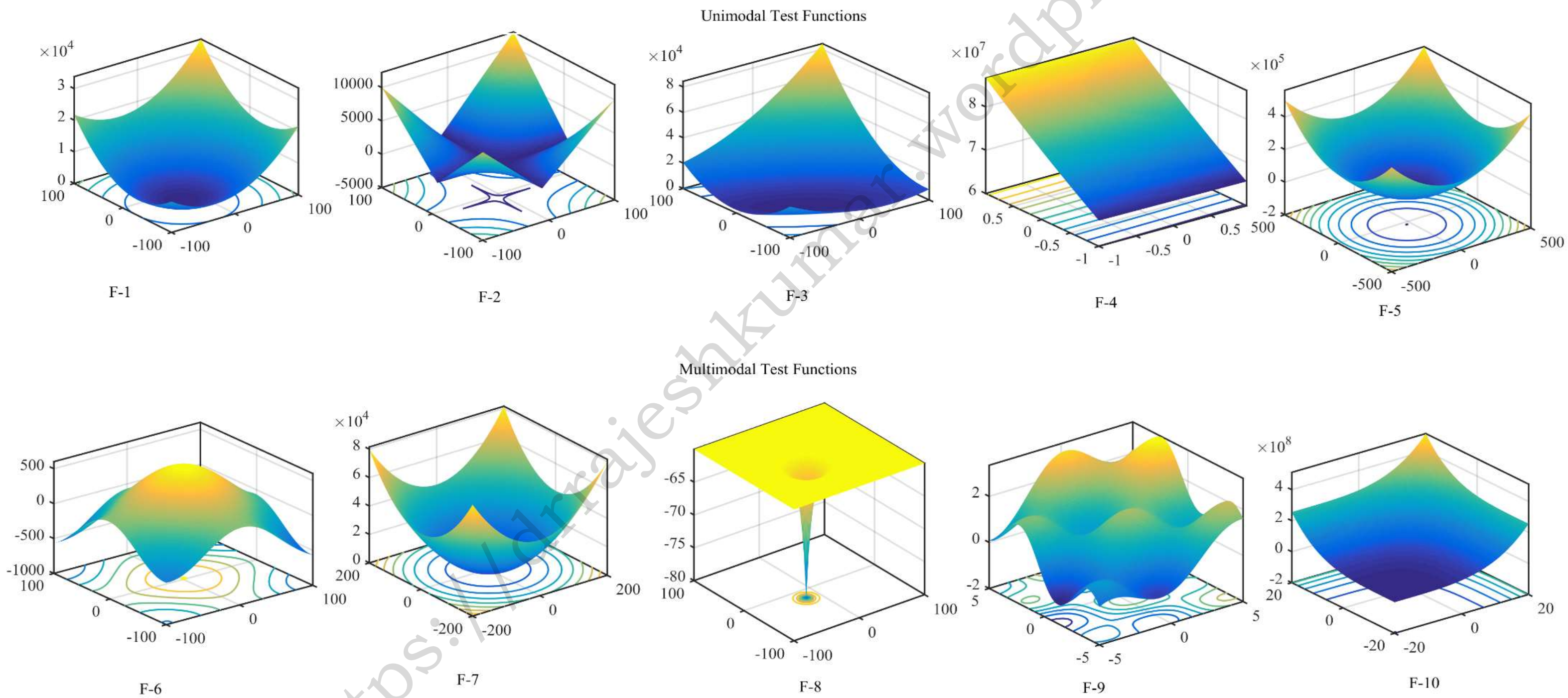
Chaotic Maps



Bench of Shifted and Biased functions

Function	Dimension	Range	Minimum value
Unimodal benchmark function			
$F_1(x) = \sum_{i=1}^{n} (x_i + 30)^2 - 50$	30	[−100, 100]	−50
$F_2(x) = \sum_{i=1}^{n} \lvert x_i + 10\rvert + \prod_{i=1}^{n} \lvert x_i + 10\rvert - 50$	30	[−10, 10]	−50
$F_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{n} x_j + 30)^2 - 50$	30	[−100, 100]	−50
$F_4(x) = \sum_{i=1}^{n-1} [100((x_{i+1} + 60) - (x_i + 60)^2)^2 + ((x_i + 60) - 1)^2] - 50$	30	[−30, 30]	−50
$F_5(x) = \sum_{i=1}^{n-1} ([(x_i + 60) + 0.5])^2 - 80$	30	[−100, 100]	−80
Multimodal benchmark function			
$F_6(x) = \sum_{i=1}^{n} -(x_i + 300)\sin(\sqrt{\lvert(x_i + 300)\rvert})$	30	[−500, 500]	−418.9829 × (32)
$F_7(x) = \sum_{i=1}^{n} [(x_i + 2)^2 - 10\cos(2\pi((x_i + 20) + 2) + 10)] - 50$	30	[5.12, 5.12]	−50
$F_8(x) = -20\exp(-0.2\sqrt{(1/n)\sum_{i=1}^{n}(x_i + 20)^2}) - \exp((1/n)\sum_{i=1}^{n}\cos(2\pi(x_i + 20))) + 20 + e - 80$	30	[−32, 32]	−80
$F_9(x) = (1/4000)\sum_{i=1}^{n} (x_i + 400)^2 - \prod_{i=1}^{n} \cos((x_i + 400)/(\sqrt{i})) + 1 - 80$	30	[−600, 600]	−80
$F_{10}(x) = (\pi/n)\{10\sin(\pi y_1) + \sum_{i=1}^{n} (y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\} + \sum_{i=1}^{n} u((x_i + 30), 10, 100, 4) - 80$	30	[−50, 50]	−80
where $y_i = 1 + (((x_i + 30) + 1)/(4))$, $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m, & x_i > a \\ 0, & -a < x_i < a \\ k(-x_i - a)^m, & x_i < -a \end{cases}$			

2D- Shapes of Bench



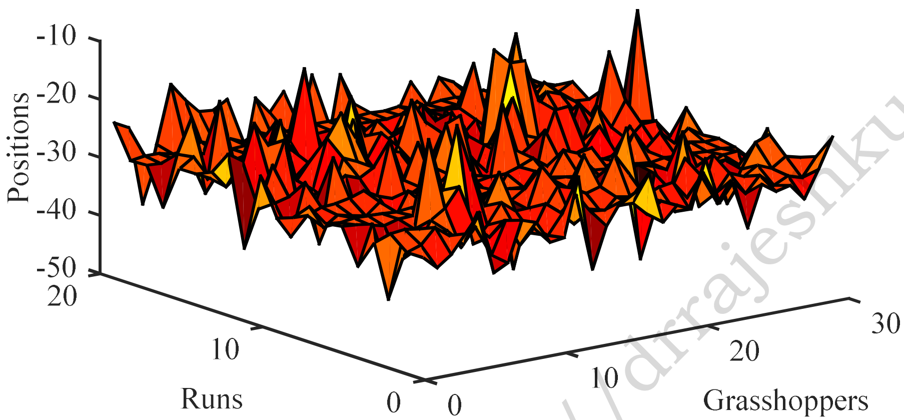
Results on Unimodal Functions (30-D)

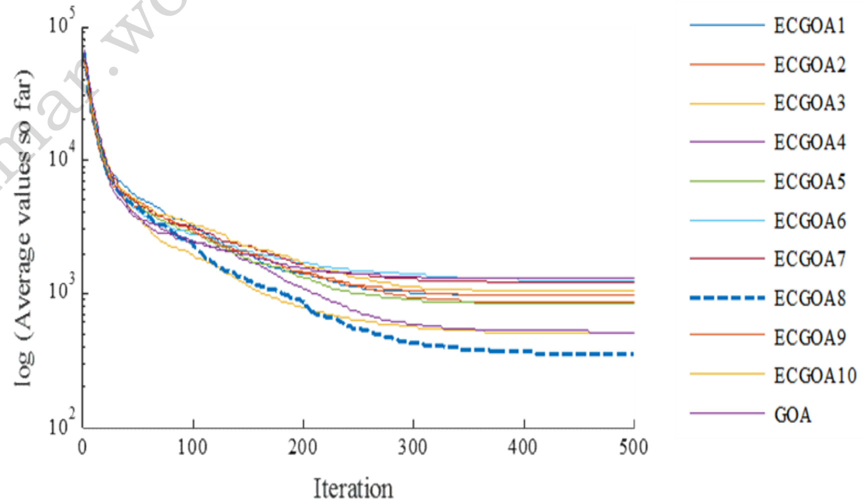
Algorithm	Statistical Parameters	UF-1	UF-2	UF-3	UF-4	UF-5
		F1	F2	F3	F4	F5
ECGOA1	Max	4.72E+03	7.441252	32384.27	5997.771	11547.22
	SD	1189.661	20.48785	8687.739	1448.595	2648.273
	Mean	9.54E+02	-34.0542	13561.55	519.9767	1515.979
	Min	-33.212	-50	3212.748	-23.8636	-49.6495
ECGOA2	Max	3.67E+03	6.983289	27021.89	774.8997	7411.605
	SD	1070.123	15.60652	7021.802	235.0562	2190.903
	Mean	8.65E+02	-33.8791	14337.61	67.54067	1770.953
	Min	-49.6441	-50	3949.875	-22.9774	-46.6215
ECGOA3	Max	2.64E+03	-10	23806.04	359978.7	4481.247
	SD	806.0854	14.47655	6705.574	80425.93	1249.42
	Mean	5.10E+02	-32.2934	11977.49	18315.61	891.0015
	Min	-49.7058	-50	1076.156	-23.1032	-45.3564
ECGOA4	Max	1.70E+03	7.013903	22406.58	5997.795	3592.651
	SD	536.6934	15.66702	5003.504	2352.145	855.4461
	Mean	5.19E+02	-30.1622	11631.74	1257.859	479.4171
	Min	-44.7163	-50	4640.106	-22.0574	-44.2489
ECGOA5	Max	5.67E+03	-10.9219	48674.12	359978.5	6140.426
	SD	1268.831	14.3114	11345.15	80389.73	1753.316
	Mean	8.38E+02	-38.4507	15310.28	18486.14	1587.872
	Min	-40.7524	-50	4158.884	-22.8343	-49.772

Results on Unimodal Functions (30-D)

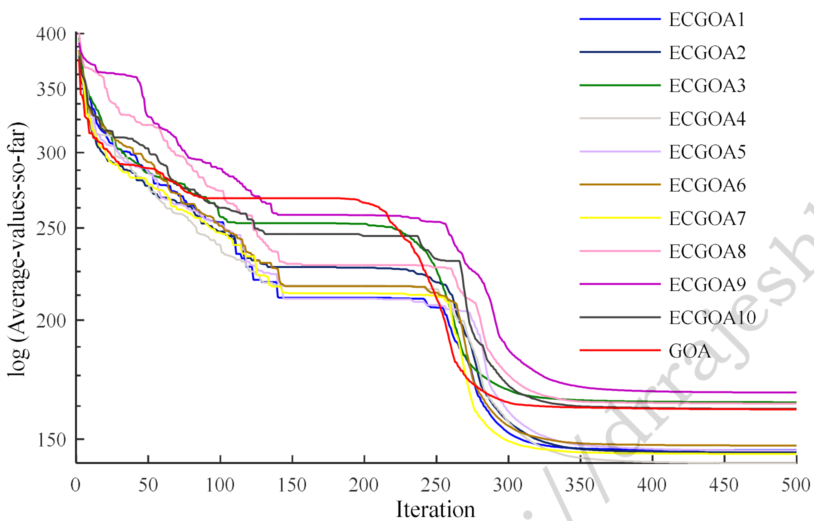
ECGOA6	Max	4.56E+03	27.11865	34182.77	359978.7	9207.069
	SD	1504.872	19.65367	7717.328	80359.56	2300.953
	Mean	1.26E+03	-35.3059	14001.46	18656.76	1582.863
	Min	-49.5997	-50	3692.072	-22.1018	-49.5038
ECGOA7	Max	4.63E+03	-30	25403.45	774.9623	9922.265
	SD	1378.628	8.3955	5469.37	333.3362	2460.44
	Mean	1.21E+03	-44.166	13289.92	179.7019	1421.978
	Min	-45.0917	-50	5563.239	-22.918	-49.0028
ECGOA8	Max	1.68E+03	5.974824	29394.74	359978.8	1992.826
	SD	480.1784	16.12038	5952.928	80354.38	486.393
	Mean	3.60E+02	-34.3295	12586.33	18679.3	411.1577
	Min	-49.5353	-50	4302.044	-23.1203	-49.105
ECGOA9	Max	6.40E+03	27.15447	35257.01	263688.6	8310.101
	SD	1522.377	20.47155	8866.673	58719	1997.682
	Mean	956.9384	-34.7665	15903.13	14423.59	1573.284
	Min	-29.154	-50	2960.342	-22.7203	7.090624
ECGOA10	Max	7.43E+03	6.999618	28524.88	3813.648	4410.677
	SD	1720.647	15.64801	6605.129	1176.846	1183.068
	Mean	1042.276	-35.9717	10828.61	360.635	1071.854
	Min	-30.8355	-50	1853.837	-23.0794	41.99444
GOA	Max	6.52E+03	-10	23228.38	5997.962	3775.516
	SD	1578.947	11.67419	5972.024	1329.84	1181.988
	Mean	1276.143	-38.4728	12189.96	554.6474	898.7971
	Min	-43.7533	-50	1178	-22.9119	-49.7339

Results of Unimodal functions (F-1)





Results of Function -7



Results on Multi Modal Functions (30-D)

Algorithm	Statistical Parameters	M-F1	M-F2	M-F3	M-F4	M-F5
		F6	F7	F8	F9	F10
ECGOA1	Max	-8904.24	271.0372	-66.5449	-29.2767	3279130
	SD	1254.676	51.23868	4.119399	13.23356	884472.8
	Mean	-11029.5	146.0832	-78.6616	-51.4071	1238399
	Min	-13826.5	66.54498	-80	-69.8688	-66.7927
ECGOA2	Max	-8832.74	229.4997	-66.7126	-28.9994	3958975
	SD	1142.206	52.12368	2.975594	11.40269	1072203
	Mean	-10745.6	145.3066	-79.171	-47.2001	1923464
	Min	-13627.7	15.85951	-80	-69.4254	-68.3447
ECGOA3	Max	-8376	222.1649	-64.3491	-39.1735	2999948
	SD	1527.962	47.29322	3.493484	10.75939	1038006
	Mean	-11293.5	164.0275	-78.9705	-60.5568	1442602
	Min	-14534.5	56.96255	-80	-78.9487	-66.9631
ECGOA4	Max	-8307.93	256.214	-78.3538	-19.0129	3999958
	SD	1109.739	57.38026	0.506681	12.7704	1292593
	Mean	-11006.9	141.5465	-79.6353	-51.0195	1278308
	Min	-12818.6	53.7245	-80	-69.8415	-72.994
ECGOA5	Max	-8540.51	243.5495	-60.3452	-28.1305	4922217
	SD	1220.617	48.63998	5.114423	13.8308	1398789
	Mean	-11059.9	146.0103	-78.1109	-47.6149	1688204
	Min	-13079.1	54.99126	-80	-69.8507	-75.9006

Results on Multi modal Functions (30-D)

ECGOA6	Max	-8426.57	249.5214	-60.0117	-39.1139	2999975
	SD	1345.302	44.48447	5.512268	11.35779	913600.2
	Mean	-10663.5	147.7425	-78.1364	-54.092	758313.7
	Min	-13323.2	72.3563	-80	-78.4344	-72.602
ECGOA7	Max	-7639.37	244.7659	-60.0035	-9.16557	3742472
	SD	1637.129	40.17972	4.45385	15.04767	1044970
	Mean	-10769.7	144.7726	-78.7532	-51.0586	1140919
	Min	-15549.9	79.90368	-80	-69.5569	-73.8642
ECGOA8	Max	-8815.14	238.5191	-78.3538	-29.0018	3999953
	SD	972.5037	39.69233	0.675579	11.76663	1258635
	Mean	-11237	163.4965	-79.6707	-50.8158	1575727
	Min	-12712	90.96168	-80	-69.9456	-68.8842
ECGOA9	Max	-7711.69	250.473	-78.3538	-19.8782	2999949
	SD	1198.213	40.70405	0.675578	12.726	778483.5
	Mean	-10681.1	167.9705	-79.6707	-41.31	1095574
	Min	-12474.2	96.95393	-80	-69.4142	-64.8591
ECGOA10	Max	-8746.85	269.3226	-60.1722	-19.3277	5249683
	SD	1190.82	41.32749	4.41648	12.70165	1582795
	Mean	-10661.7	161.4352	-78.7616	-43.6748	1394908
	Min	-13545.7	84.36102	-80	-69.0206	-61.9252
GOA	Max	-9225.8	258.3774	-60.0393	-20.1744	3000918
	SD	1292.871	50.35495	8.248127	12.85493	975411.2
	Mean	-11237.6	161.2432	-75.4165	-57.6119	1122615
	Min	-14022.9	76.48267	-80	-69.8943	-69.4996

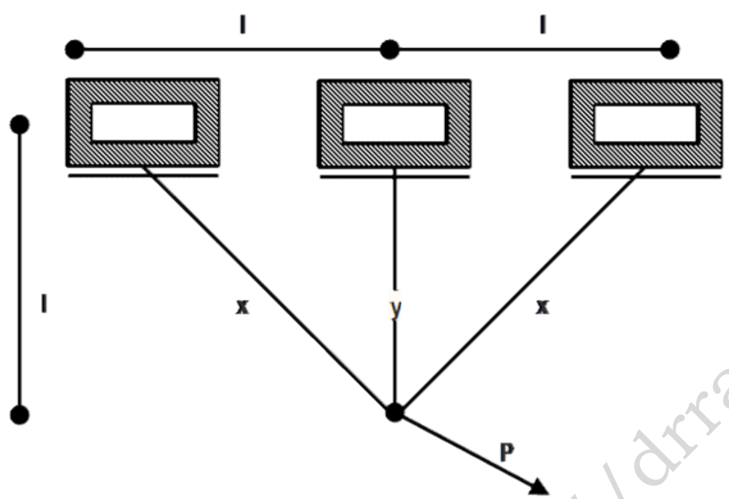
Results of Wilcoxon Rank-Sum Test (Unimodal)

Function	F1	F2	F3	F4	F5
ECGOA1	0.036048	0.169275	0.967635	0.6359	0.3683
ECGOA2	0.147847	0.013881	0.336915	N/A	0.0540
ECGOA3	0.881731	0.007431	0.989209	0.8817	0.9533
ECGOA4	0.228694	0.000986	N/A	0.1404	0.4755
ECGOA5	0.081032	0.166588	0.524987	0.4094	0.7590
ECGOA6	0.072045	0.088317	0.409356	0.9892	0.4340
ECGOA7	0.014364	N/A	0.310402	0.6554	0.9423
ECGOA8	N/A	0.04359	0.797197	0.5792	N/A
ECGOA9	0.15557	0.14484	0.163596	0.1719	0.4971
ECGOA10	0.126431	0.043738	0.490334	0.3793	0.9917
GOA	0.014364	0.07045	0.755743	0.0036	0.0266

Results of Wilcoxon Rank-Sum Test (Multimodal)

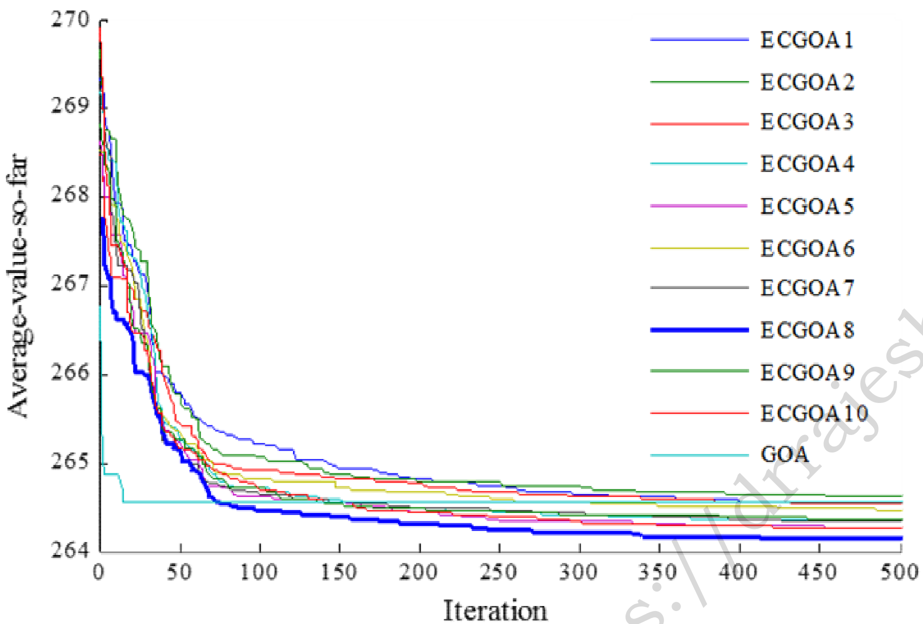
Function	F6	F7	F8	F9	F10
ECGOA1	0.56	0.776391	0.27	0.03	0.08
ECGOA2	0.2	0.542772	0.73	8.36E-04	8.36E-04
ECGOA3	0.81	0.14042	0.0098	N/A	0.02
ECGOA4	0.59	0.655361	N/A	0.02	0.23
ECGOA5	0.88	0.507505	0.041	0.040	0.019
ECGOA6	0.22	0.71498	0.0114	0.0909	N/A
ECGOA7	0.19	0.126431	0.525	0.0337	0.085
ECGOA8	0.9892	N/A	0.2503	0.0207	0.02
ECGOA9	0.23	0.113551	0.285	5.85E-06	0.0601
ECGOA10	0.14	0.163596	0.6554	1.99E-04	0.081
GOA	N/A	0.0208454	0.0239	0.0076	0.01719

Three Truss Bar design Problem



- Three truss bar design problem is a well-known engineering design problem and has been used for benchmarking of many problems.
- The objective of this problem is to minimize the volume (X) by adjusting cross sectional area (x, y) as per equations subject to the constraints.
- This objective function is nonlinear in nature and possess three nonlinear constraints which contains stress parameter.
- For solving this optimization problem, no. of search agents (30) and maximum iterations count (500) are considered and kept constant for all the variants.

Results on Three Truss Bar Design



Algorithm	Max	Mean	Min	SD
ECGOA1	266.5823	264.5394	263.8976	0.851265
ECGOA2	268.235	264.6162	263.8974	1.107169
ECGOA3	268.0221	264.5413	263.896	1.202524
ECGOA4	266.4968	264.3473	263.8961	0.76741
ECGOA5	265.6408	264.2707	263.8963	0.513983
ECGOA6	266.5492	264.4754	263.897	0.739352
ECGOA7	268.1783	264.3391	263.8971	0.936519
ECGOA8	265.4146	264.1322	263.8965	0.401496
ECGOA9	268.8148	264.3604	263.8962	1.108937
ECGOA10	266.0352	264.2575	263.8961	0.562701
GOA	265.528	264.3357	263.3274	0.57364

Frequency Modulated Sound Wave Parameter Estimation:

Parameter estimation of Frequency Modulated synthesizer is a six dimensional optimization problem and a part of FM sound wave synthesis. The problem is formulated as the parameter estimation for generation of the sound as per the target sound. The problem is complex and multimodal in nature. Variable range (-6.4,6.35)

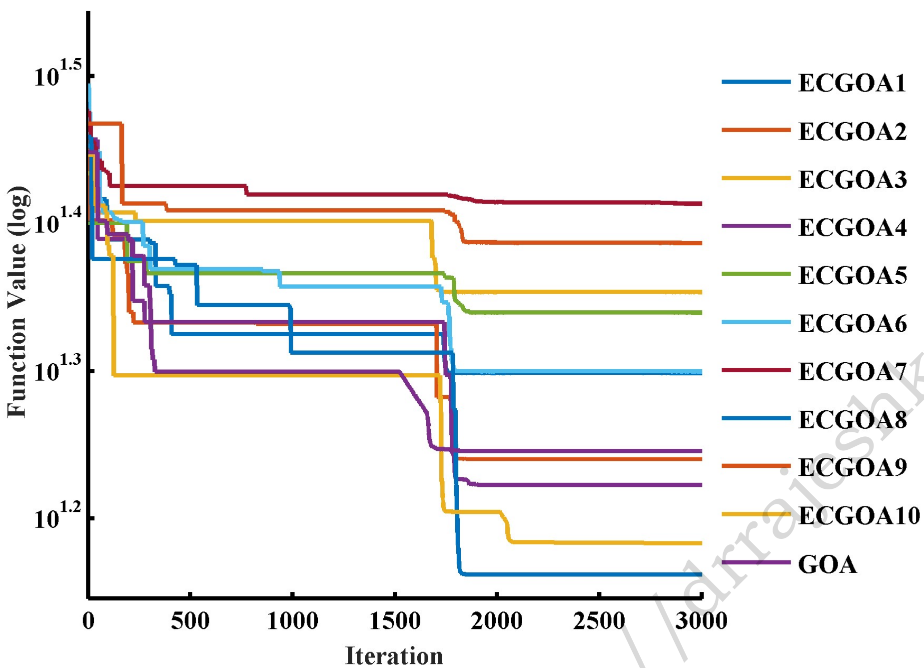
$$X = \{a_1, \omega_1, a_2, \omega_2, a_3, \omega_3\}$$

$$y(t) = a_1 \sin(\omega_1 t\theta + a_2 \sin(\omega_2 t\theta + a_3 \sin(\omega_3 t\theta)))$$

$$y_0(t) = (1.0)\sin\Big((5.0)t\theta - (1.5)\sin\big((4.8)t\theta\big) + (2.0)\sin((4.9)t\theta)\Big)$$

$$Min\ f = \sum_{t=0}^{100} (y(t) - y_0(t))^2$$

Results on FM Sound Wave Synthesis



Algorithms	Min	Max	Mean	SD
ECGOA1	14.048	26.720	20.748	2.754
ECGOA2	8.416	25.560	20.266	4.067
ECGOA3	11.407	27.283	20.652	4.335
ECGOA4	0.00000014	27.280	19.863	5.439
ECGOA5	8.416	27.354	20.708	4.771
ECGOA6	8.416	26.522	19.687	5.183
ECGOA7	10.177	25.913	18.830	4.596
ECGOA8	0.000	26.999	19.108	5.710
ECGOA9	11.549	27.123	20.896	4.064
ECGOA10	13.393	27.462	21.266	3.890
GOA	8.416	26.745	20.110	4.673
CPSOH	3.45	42.52	27.08	60.61
GWO	1.9311	26.03	25.1633	5.9177
TRIBES-D	2.22	22.24	14.68	4.57
CGSA	8.4161	24.71	17.43	4.1609
G-CMA-ES	3.326	55.09	38.75	16.77

Conclusion

- Exploration and exploitation phases of a metaheuristic algorithm are connected with a bridging mechanism. The efficacy of this bridging mechanism is important to have better convergence characteristics, solution quality and optimization performance.
- 10 different chaotic maps have been embedded with the conventional GOA parameter ‘c’ and chaotic mechanisms have been proposed. These mechanisms enable exploration phase till last iteration with chaotic properties.
- Ten shifted and biased bench mark functions have been considered to benchmark the problems. The proposed variants have been evaluated on 30-dimension and 50-dimension (in Paper) bench mark problems
- The application of these variants on three truss bar design problem and parameter estimation of frequency modulated sound wave synthesis problem have also been investigated.
- It is observed that the performance of the developed variants is competitive to other contemporary algorithms. In some cases, variants outperform.