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Physical and Physic-Chemical Based Optimization Methods: A Review

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ABSTRACT

Optimization techniques can be divided to two groups: Traditional or numerical methods and methods based on stochastic. The essential problem of the traditional methods, that by searching the ideal variables are found for the point that differential reaches zero, is staying in local optimum points, can not solving the non-linear non-convex problems with lots of constraints and variables, and needs other complex mathematical operations such as derivative. In order to satisfy the aforementioned problems, the scientists become interested on meta-heuristic optimization techniques, those are classified into two essential kinds, which are single and population-based solutions. The method does not require unique knowledge to the problem. By general knowledge the optimal solution can be achieved. The optimization methods based on population can be divided into 4 classes from inspiration point of view and physical based optimization methods is one of them. Physical based optimization algorithm: that the physical rules are used for updating the solutions are:, Lighting Attachment Procedure Optimization (LAPO), Gravitational Search Algorithm (GSA) Water Evaporation Optimization Algorithm, Multi-Verse Optimizer (MVO), Galaxy-based Search Algorithm (GbSA), Small-World Optimization Algorithm (SWOA), Black Hole (BH) algorithm, Ray Optimization (RO) algorithm, Artificial Chemical Reaction Optimization Algorithm (ACROA), Central Force Optimization (CFO) and Charged System Search (CSS) are some of physical methods. In this paper physical and physic-chemical phenomena based optimization methods are discuss and compare with other optimization methods. Some examples of these methods are shown and results compared with other well known methods. The physical phenomena based methods are shown reasonable results.

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1. Introduction

Optimization is based on this mathematical idea that to determine the decision variables of a function so that the function should be in optimum value (minimum or maximum).

There are a wide range of optimization methods in science and engineering application. Different researchers used different methods. This wide range covers so many technical problems such as cable ampacity, DG placement renewable energy and power quality [1–51]. Most of optimization methods are based on different mathematical ideas, physical and physic-chemical process or on natural behavior in nature or behavior of animals and insects [52–92].

Our goal in this review paper is to discuss the physical and physic-chemical based optimizations methods.

Some of these methods are single-objective optimization algorithm [40] and others are multi objective optimization algorithm [41]. These algorithms are:

1.1. Lightning attachment procedure optimization algorithm

Foroughi et al [40,41] mimic lightning attachment approach including movement of downward leader and upward leader of lightning, unpredictable behavior (trajectory) of downward leader of lightning and branch fading of lightning. The optimum result is striking point of lightning. This procedure applied for both single objective optimization [40] and multi-objective optimization [41]. In these papers the authors mentioned following benefits for their method: - the method is not dependent on parameters tuning. - The method can solve challenging, high constraint and discrete optimization cases. – Can be used for both single and multi-objective problems. Main procedure of LAPO algorithm is shown in Fig 1.

In [40,41], this method applied to 34 different benchmark test function and the result compared with 9 other optimization method. In order to compare this method with other methods, these method implemented on different problems including discreet, continuous, high dimension, and high constrains problems. The comparisons are done from different point of view as finding global optimum point, robustness, quality of results, and CPU time consumption.

In [40] the result that obtained by Lightning Attachment Procedure Optimization Algorithm compared with 9 other optimization method including: 1- Artificial Bee Colony (ABC) [76], 2- Differential Evolution (DE) [87], 3- Shuffled Frog Leaping Algorithm (SFLA), 4- Imperialist Competitive Algorithm (ICA), 5- Particle Swarm Optimization (PSO), 6- Ant-Lion Optimizer (ALO), 7- Gray Wolf Optimizer (GWO), 8- Cuckoo Search Algorithm (CSA), 9- Firefly Optimization Method (FOM), and 10- Lightning Search Algorithm (LSA).

Benchmark test functions that used in [40] include five groups: 1- unimodal, 2- multimodal, 3- fixed-dimension multimodal, and 4- composite functions, 5- classical engineering design problems.

unimodal test function has utilized to evaluate the performance of local search of optimization method. Unimodal test function have a simple function with convex shape. Each method that obtain better results in these functions, has better performance in local search. The obtained result in [40] shows that LAPO has Superiority and high quality performance in solving unimodal problems compared to other methods.

The multimodal and fixed-dimension multimodal test functions are testified in [40] for evaluating the ability of the method in finding global optimum point. Result shows that LAPO method has excellence performance in finding global optimum when problems has several local optimum.

The composite benchmark test functions are the fourth group of test functions that utilized in [40] to examine the ability of LAPO in global and local search simultaneously. From obtained result in [40] it can be concluded that LAPO has good quality in finding global optimum point and rarely get stuck on local optimum points.

Step 1: Initialize Random Test Point

Step 2: Downward Leader Movement toward Ground

Step 3: Calculate Electric Field below the Cloud

Step 4: Moving Test point toward maximum Electric field

Step 5: Determine Next jump and maximum Electric Field

Step 6: Upward leader Movement

Step 7: Final Jump and Touching Upward Leader and Downward (Global optimal Point)

Fig. 1. Main Step of LAPO algorithm.

1.2. Charged system search (CSS) optimization algorithm

Kaveh et al [56] introduced a new algorithm for optimization based on physical and mechanical principles that called Charged System Search (CSS). The Coulomb law of electrostatics and Newton laws from mechanics. In this algorithm, each search agent known as a charge. Every search agent applying force to the other search agent based on their charge and the distance between them. And every search agent affected by this force begins to move and the new position of charge of each charge is determined by the speed and force applied to this search agent. The authors claimed their method has good performance in compare to other evolutionary algorithms. Main procedure of CSS algorithm is shown in Fig 2.

In [56], CSS implemented on 17 mathematical test function and 4 engineering designing problem. The result that obtained by CSS compared with 4 type of modified Genetic Algorithm. The obtained results shows that this method not only has fast convergence but also has good quality.

Step 1: Initialize Random Charge Position and Assign the Initial Velocities
Step 2: Determine Charge New Positions Based on their Previous Positions and Velocities
Step 3: Compute Fitness of each charge particle
Step 4: Updating Velocities and Position of each charge Particle Based on their attracting Force
Step 5: Determine Particle with Maximum Attracting Force

Fig. 2. Main Step of CSS algorithm**.**

1.3. Central force optimization (CFO) algorithm

Formato [57] introduced a new optimization algorithm which is based on the metaphor of gravitational kinematics. In the procedure of this algorithm, a random number is not used. in this method, search agents(probe) are flying around search space and under the influence of gravity of other objects change their position. With increasing iteration, all search agents will be attracted in close orbits of big masses with largest gravitational field. Main procedure of CFO algorithm is shown in Fig 3.

Author claimed his method is easily implemented in a compact computer program and showed very good performance.

In [57] CFO used to obtain the optimum point of 5 test functions. Results that obtained by this method are not compared with other optimizations method. CFO is not a parameter free algorithm and needed to tune parameters. Arbitrary changing of these parameters can lead to bad results.

Step 1: Initialize Random Probe Position and Assign the Initial Accelerations
Step 2: Determine Probe New Positions Based on their Previous Positions and Accelerations
Step 3: Compute Kinematics and Gravitational Field of each charge particle
Step 4: Updating Acceleration and Position of each charge Particle
Step 5: Determine Particle with Maximum Kinematics and Gravitational field

Fig. 3. Main Step of CFO algorithm.

1.4. Artificial chemical reaction optimization algorithm (ACROA)

Chemical reaction is known as a process which leads to transfer one st of chemical substances to another. Author [58] used chemical reaction to introduce a new optimization algorithm. In this algorithm, each particle of the population is considered as the reactant and each reactant collides with other reactants and this collision causes chemical reactions. Author claimed that his algorithm easily can be adapted to multi-objective optimization cases. Main procedure of ACRO algorithm is shown in Fig 4.

This method is free from parameter tuning and authors claimed this method has fast convergence and shorter computation time. ACROA implemented on 3 different test functions in [58] and obtained results compared with Artificial Bee Colony optimization method (ABC) and Biogeography optimization algorithm. Results shows ACROA has better performance than ABC.

Step 1: Initialize Parameter and reactants
Step 2: Applying Chemical Reaction
Step 3: Updating Reactants Positions based on type of reactions
Step 4: Termination Criterion Check.

Fig. 4. Main Step of ACRO algorithm.

1.5. Black hole (BH) optimization algorithm

Hatamlou [59] is used black hole phenomenon to introduce a optimization algorithm. Same as population based methods BH algorithm begins with an initial population of candidate solutions to an optimization case and an objective function which is calculated for them. In this algorithm, the best-obtained result at each iteration considered as a black hole and other solutions is considered to be stars. each star will be attracted by black hole and if the new position of the star is near than specific value to the black hole, it will be destroyed and new stars will be born in search space. The author claimed that BH algorithm outperforms other traditional heuristic algorithms for several benchmark datasets. Main procedure of BH algorithm is shown in Fig 5.

BH is free from tuning any parameter and has a simple structure for implementation. BH implemented on 6 different test functions in [59] and achieved results compared with Gravitational search algorithm (GSA), Particle Swarm Optimization (PSO) and Bang-big Crunch algorithm.

Step 1: Initialization of Stars.
Step 2: Evaluate Fitness of each Star.
Step 3: Selecting star with best Fitness as Black Hole.
Step 4: Determining position of each Star based on their interactions.
Step 5: Determine Position of best Star as the Black Hole.
Step 6: Stopping Criteria

Fig. 5. Main Step of BH algorithm.

1.6. Ray optimization (RO) algorithm

Kaveh et al [60] used Snell's light refraction law to introduce a new optimization algorithm and this law is the main tool of RO algorithm. The inspiration of this algorithm is ray refraction from one transparent material to the other. In this algorithm authors used Snell's light refraction law for updating and determining the movement of search agents in search space. Eventually, refracted rays converged to a point that is known as global optimum.Authors claimed that RO algorithm has a good efficiency and can be utilized for structural optimization problems. Main procedure of RO algorithm is shown in Fig 6.

In [60], RO implemented on 17 mathematical test function and 5 engineering problem. The result that obtained by RO compared with Genetic Algorithm. The obtained results shows that RO method outperforms GA for all the test function.

Step 1: Initialize position of Ray particles

Step 2: Calculate the fitness of each particle

Step 3: Calculate the refraction factor of each particle

Step 4: determine the movement vector and motion refinement

Step 5: Update position of each particle

Step 6: introduce lighter particle as the best solution

Fig. 6. Main Step of RO algorithm.

1.7. Galaxy-based search algorithm (GbSA)

Author [62] a novel optimization method from nature is employed to explore the search space for optimum solution to principal components analysis problem. This algorithm is inspired from spiral arm of spiral galaxies. in this algorithm by using the concept of the spiral arm of spiral galaxies and combining this concept with chaos, the global optimum point is found. Author claimed that his method shows good results with respect to other methods. Main procedure of GbSA algorithm is shown in Fig 7.

Step 1: Creation of Universe

Step 2: Calculation of Each Body Mass

Step 3: Calculation of Gravitational Force

Step 4: Decreasing of Number of Body

Step 5: Searching for Local Improvement of each universe

Step 6: Stopping Criteria

Fig. 7. Main Step of GbSa.

1.8. Water evaporation optimization (WEO) algorithm

Authors [63] developed a new physical inspired non gradient algorithm to solve global optimization problems. WEO algorithm mimics the evaporation of a tiny layer of water on the solid surface with different wettability which can be studied by molecular dynamics simulations. In WEO each Water molecules considered as a search agent in the optimization algorithm. Solid surface or substrate with variable wettability is known as the search space. The surface wettability reducing means that water molecules gathered to several points as the water droplets. Decreasing the surface wettability is a good sign of approaching the target point in minimization problems. The evaporation flux rate of the water molecules is used as the most proper parameter for calculation of the position of the particles. The authors claimed their optimization algorithm is an effective and comparable tool. Main procedure of WEO algorithm is shown in Fig 8.

In [63], WEO applied to 13 different benchmark test function and the result compared with Bat Algorithm (BA) and PSO. Benchmark test functions that used in [63] include three groups: 1- unimodal, 2- multimodal, 3- classical engineering design problems. The obtained results by WEO indicated that this method have good performance in solving optimizations problem.

Step 1: Initialize Randomly Position of each Water Molecules.

Step 2: Generating Water Evaporation matrix

Step 3: Generating Random Permutation based step Size Matrix

Step 4: Generating Evaporated Water molecules and updating the matrix of of water molecules.

Step 5: Stopping Criteria

Fig. 8. Main Step of WEO algorithm**.**

1.9. Multi-verse optimizer (MVO) algorithm

Mirjalili et al [65] introduce an algorithm which is used a novel nature inspired algorithm called Multi-Verse Optimize. The essential of this algorithm are according to three definition in cosmology: White hole, Black hole and wormhole. In this algorithm, each search agent considered as the universe that interacts with other universes. For each universe inflation rate calculated and the position of them updated based on this factor. The universe that has higher inflation is considered to have a white hole and the universe that has lower inflation is considered to have a black hole. Two different universes transfer objects from the tunnel that created between them. In addition, each universe has wormholes that transferred objects between two universes without considering their inflation rate. Authors claimed that MVO algorithm showed its potential in solving real cases with unknown search spaces. Main procedure of MVO algorithm is shown in Fig 9.

MVO implemented on 19 mathematical challenging test function in [65]. The results that obtained by MVO compared with 4 well known optimization method such as GSA, PSO, GWO and GA. The obtained result shows that MVO has a good performance and it can outperforms other heuristic algorithms.

Step 1: Initialize Randomly Universes
Step 2: Evaluate Fitness (Inflation rate) of Each Universes and normalize it
Step 3: Update position of each universe (white hole) based on wormhole existence probability (WEP) and travelling distance rate (TDR).
Step 4: Determine Position of Black Hole as the Best Solution
Step 5: Stopping Criteria

Fig. 9. Main Step of MVO algorithm.

1.10. A gravitational search algorithm (GSA)

Rashedi et al [66] based on the law of gravity and mass interactions introduced an new optimization algorithm. In this algorithm the searcher agents are a set of masses which interact with each other based on the Newton's law of gravity and laws of motion. Each search agent applying force the other agent proportional to weight and inversely proportional to the square of the distance between them. In this algorithm the quality of each search agent measured by its mass. the heaviest search agent in the population is known as global optimum. Authors claimed that their method shows high performance in solving various nonlinear functions. Main procedure of GSA algorithm is shown in Fig 10.

GSA applied to 23 different benchmark test function and the result compared with CFO, GA and PSO. Benchmark test functions that used in [63] include four groups: 1- unimodal, 2- multimodal, 3- composite functions 4- classical engineering design problems. The obtained results by GSA shown that this method have good performance in solving optimizations problem.

Step 1: Initialize Randomly Position of Each Mass
Step 2: Evaluate Fitness of Each Mass
Step 3: Update Best and Worst of Mass Group
Step 4: Calculate total force of Each Mass in different Direction
Step 5: Calculate Velocity and Acceleration of Each mass at each direction
Step 6: Stopping Criteria

Fig. 10. Main Step of GSA.

2. Comparative study

In this section, the results of the each algorithm is compared from different points of views. Three test functions are utilized to compare the performance of each method. These test functions can be classified in different categories consist of 1- unimodal, 2- multimodal, 3- hybrid-multimodal and 4-composite functions. In the first part of comparison, 4 test functions which are used in [40,63,65,66] are illustrated to compare the ability of the physics based method compared to other methods. These benchmark functions are illustrated in tables 1 and 2, respectively.

Table 1
Benchmark functions.

Function	Dim	Range	fmin	Type
$F_1(x)=\sum_{i=1}^{n-1}\{100(x_{i+1}-x_i)^2+(x_i-1)^2\}$	30	[-30,30]	0	Unimodal
$F_2(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	30	[-500, 500]	0	Multimodal
$F_3(x)=\sum_{i=1}^{11}[a_i-\frac{x_1(b_i^2+b_i x_2)}{b_i^2+b_i x_3+x_4}]$	4	[-5,5]	0.00030	Fixed-dimension multimodal

The obtained result by a physics-based optimization algorithm shown that these methods could close to the optimum point. The results of the implementation of the physical algorithms on unimodal functions show that this algorithm performs better than other methods. As shown in table 2, the best-obtained result is for the physical-based optimization method. Therefore, it can be stated that physical-based algorithms have better performance in solving unimodal functions. Second test function is multimodal test functions. As shown in Table 1, the two algorithms reach the exact optimal point of multimodal test functions. Type of third test function is Fixed-dimension multimodal. This type of test functions examines the ability of optimization algorithms on balancing between exploration and exploitation phase. Achieved result by physical-based algorithms shown that physical-based optimization methods could well balance between exploration and exploitation. Variables obtained by each algorithm is shown in Table A1.

3. Conclusion

In this paper, physic based optimization methods reviewed. These methods are inspired from physical phenomena. Firstly, the physic that algorithms inspired by that was explained. then steps that implement in each algorithm briefly discussed. At the end of this paper, physical-based optimizations are applied to 3 different types of test functions and achieved results showing that this method have good performance in solving optimizations problem.

Table 2
Results of different method for solving test functions.

Method	Function	Best	Average	Std
LAPO	F1	19.5667	22.7427	0.6846
	F2	0	1.53344	3.70144
	F3	3.0749E-04	5.5811E-04	2.2495E-04
CSS	F1	28.6514	125.12	61.2
	F2	0.076628	0.275	0.0174
	F3	0.00421	0.0974	0.014
CFO	F1	28.7599	133.5	61.01
	F2	0.7351	29.36	5.89
	F3	0.154	1.262	0.315
RO	F1	28.8219	101.114	52.14
	F2	0.34258	2.1658	0.4569
	F3	0.00548	0.1578	0.0541
BH	F1	60.002	98.215	15.843
	F2	4.33E-04	3.124E-2	1.054E-2
	F3	4.15E-3	0.325	0.0945
GbSA	F1	69.0119	114.174	31.456
	F2	1.9854	8.145	2.1465
	F3	0.00457	1.645E-1	7.255E-3
GSA	F1	-	25.16	-
	F2	-	15.32	-
	F3	-	8E-03	-
MVO	F1	-	1272.13	1479.477
	F2	-	118.046	39.34364
	F3	-	30.00705	48.30615
WEO	F1	1.347	22.042	16.765
	F2	0	0.265	0.768
	F3	-	-	-
PSO	F1	160.6205	1.4821E+03	1.7592E+03
	F2	44.6941	84.6695	22.4398
	F3	3.0750E-04	0.0056	0.0084
GWO	F1	36.0767	37.0454	0.8404
	F2	5.6843E-05	3.1699	6.6764
	F_3	3.0846E-04	0.0033	0.0069

The results of application physic based optimization on benchmark test functions reveal that these methods have fast convergence and excellence quality in solving high dimensions and hard problems. In this paper ten different physic based optimizations are collected and their inspirations briefly explained. In addition to that, for each method, the details of the test functions are illustrated. At the end, some examples of these methods are shown and results compared with other well-known methods. Result show that these physical based methods have high quality in solving complicated optimization problems.

Appendix A

Table A1
Obtained variable by physical optimization algorithms.

F1					F2				
CSS	CFO	RO	BH	GbSA	CSS	CFO	RO	BH	GbSA
1.1E-01	5.24E-03	-2.50E-04	1.59E-01	-5.84E-02	-5.0E-04	1.4E-02	-8.1E-03	3.5E-04	-1.7E-02
5.13E-03	7.02E-03	6.87E-03	1.92E-01	-2.17E-01	6.9E-03	-8.2E-03	6.4E-03	1.9E-04	-5.1E-03
1.36E-03	1.12E-02	5.19E-04	-3.12E-02	6.63E-02	2.4E-03	-1.2E-02	-6.3E-03	3.1E-04	7.7E-03
9.76E-03	6.24E-03	7.83E-03	6.66E-02	-1.74E-01	-1.1E-03	3.4E-03	-3.3E-03	-9.5E-05	-1.7E-03
1.54E-02	7.25E-03	9.95E-04	-1.14E-01	-6.93E-03	8.7E-04	-6.5E-03	1.4E-02	6.4E-04	-5.4E-03
-2.83E-03	4.30E-03	-6.54E-04	1.73E-01	-9.89E-02	1.8E-03	-1.4E-02	-1.5E-02	3.1E-04	-1.9E-02
8.00E-04	1.08E-02	1.41E-03	9.25E-02	-4.56E-02	3.7E-03	1.8E-02	5.7E-03	-4.3E-04	9.2E-03
3.73E-03	1.38E-02	-2.39E-03	1.04E-01	-6.56E-02	-2.6E-03	4.3E-03	3.0E-03	-1.8E-04	-1.2E-02
9.34E-04	3.41E-03	2.06E-03	-8.02E-02	-1.31E-01	3.1E-04	9.9E-03	-3.5E-03	8.0E-05	-2.7E-03
1.21E-02	1.12E-02	2.55E-03	-1.12E-01	-1.54E-02	-4.2E-03	-1.2E-02	4.5E-03	-1.1E-04	-2.1E-03
1.31E-02	1.11E-02	2.05E-03	1.61E-01	-2.10E-01	-2.8E-03	7.9E-03	4.8E-03	-4.0E-04	-1.4E-02
1.26E-02	5.04E-03	9.53E-03	1.29E-01	1.93E-01	4.1E-03	1.2E-02	-4.6E-03	4.1E-05	-6.1E-04
6.93E-03	1.21E-02	4.13E-03	-6.42E-02	1.31E-01	-2.4E-03	-1.1E-02	4.8E-03	2.5E-06	1.9E-02
1.70E-02	1.06E-02	9.18E-03	-1.67E-01	-1.40E-01	-5.5E-04	-1.6E-02	-5.6E-04	-2.2E-04	3.9E-03
8.24E-03	9.65E-03	3.70E-03	5.32E-02	1.64E-01	5.6E-03	-4.4E-03	1.3E-02	-1.5E-04	2.2E-02
9.58E-03	8.00E-03	2.06E-03	1.06E-01	-5.38E-02	-5.8E-03	-5.4E-03	3.5E-03	1.4E-04	1.0E-02
8.33E-03	4.48E-03	1.17E-03	9.33E-02	9.38E-02	-2.4E-03	3.2E-03	4.4E-03	3.1E-04	-1.7E-02
-1.04E-03	5.02E-04	-2.83E-04	7.84E-02	-2.54E-02	-8.4E-03	3.7E-03	6.2E-03	1.4E-04	3.4E-03
7.80E-03	1.15E-02	3.61E-03	-4.58E-02	3.43E-02	6.1E-03	2.4E-03	-2.6E-04	4.7E-05	-6.0E-03
-4.42E-04	4.60E-03	2.00E-03	-7.29E-02	3.80E-03	-3.6E-03	-1.8E-02	-4.3E-03	-3.0E-04	-9.7E-01
1.68E-03	6.69E-03	3.91E-03	-6.07E-02	-2.63E-01	2.5E-04	7.9E-03	-1.8E-03	2.0E-04	-2.0E-02
-1.62E-03	1.41E-02	5.86E-03	1.60E-01	6.46E-02	6.0E-04	-2.1E-02	1.4E-03	2.6E-05	-1.6E-02
5.15E-04	6.39E-03	3.16E-03	2.99E-02	4.62E-02	7.8E-04	9.2E-03	-5.2E-03	-6.5E-04	-6.3E-03
-2.04E-03	1.40E-03	4.77E-03	8.79E-02	7.40E-02	1.9E-03	1.4E-02	-1.3E-02	-4.3E-05	-1.8E-02
8.90E-03	2.69E-03	4.16E-04	-1.03E-01	9.77E-02	9.3E-04	7.1E-04	1.2E-02	-4.7E-05	-1.3E-02
8.80E-03	6.51E-03	7.21E-03	6.14E-02	3.70E-02	-3.3E-03	8.9E-03	-7.2E-03	-3.3E-04	-1.6E-02
5.21E-03	1.15E-02	3.47E-04	1.72E-01	-1.16E-01	-1.3E-03	1.8E-02	-4.9E-03	1.4E-04	-1.9E-02
5.33E-03	1.15E-02	-4.62E-05	5.55E-02	1.38E-01	-2.7E-03	-7.7E-03	1.5E-02	-7.2E-05	-6.8E-03
1.31E-02	5.98E-03	1.37E-02	-1.39E-01	-6.89E-02	-5.4E-03	-7.5E-03	3.6E-03	-3.3E-04	-1.7E-03

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