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COMPARATIVE ASSESSMENT OF LIGHT-BASED INTELLIGENT SEARCH AND OPTIMIZATION ALGORITHMS

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ABSTRACT

Classical optimization and search algorithms are not effective for nonlinear, complex, dynamic large-scaled problems with incomplete information. Hence, intelligent optimization algorithms, which are inspired by natural phenomena such as physics, biology, chemistry, mathematics, and so on have been proposed as working solutions over time. Many of the intelligent optimization algorithms are based on physics and biology, and they work by modelling or simulating different nature-based processes. Due to philosophy of constantly researching the best and absence of the most effective algorithm for all kinds of problems, new methods or new versions of existing methods are proposed to see if they can cope with very complex optimization problems. Two recently proposed algorithms, namely ray optimization and optics inspired optimization, seem to be inspired by light, and they are entitled as light-based intelligent optimization algorithms in this paper. These newer intelligent search and optimization algorithms are inspired by the law of refraction and reflection of light. Studies of these algorithms are compiled and the performance analysis of light-based intelligent optimization algorithms on unconstrained benchmark functions and constrained real engineering design problems is performed under equal conditions for the first time in this article. The results obtained show that ray optimization is superior, and effectively solves many complex problems.

Keywords: optimization, optics inspired optimization, ray optimization, artificial intelligence

1. INTRODUCTION

Optimization is present everywhere in our lives – from engineering to industrial design, from business planning to travel planning [1]. Optimization has played an even more important role in our lives recently. Evolutionary and population-based optimization methods are very popular and widely used in many engineering fields [2]. These optimization techniques choose the best of the many available options intelligently, and they provide a suitable environment for the solution of problems [1]. Most optimization algorithms require a mathematical model for the system model. Establishing a mathematical model for complex systems is often difficult. Even if the model is established, the solution time cannot be used due to the huge cost [3]. That is, the design of an optimization algorithm has a challenging process, which is caused by physical events to obtain appropriate global and local search operators [2].

Classical optimization methods may be insufficient and unsuitable for solving complex nonlinear large scaled search and optimization problems. Classical methods are not effective in adapting them to the problems of interest. This, in many cases, requires some assumptions that may be difficult to confirm. Often, due to the natural solution mechanisms of solving classical search methods, the problem concerned is modelled such that the method will manage it. The strategy for solving classical methods usually depends on the types of objectives and constraints, as well as on the types of decision variables. Their effectiveness also strongly depends on search space, the number of constraints, and the number of decision variables. Another important shortcoming is that they do not stand for common target strategies for different types of constraint functions and variables. In other words, classical methods solve models that have a specific type of objective function or constraint functions. However, many optimization problems, such as management, sports, engineering, economy, computer require concurrent different types of objective functions, constraint functions, and decision variables, simultaneously. Intelligent optimization and search algorithms are proposed and efficiently used in many different fields, because they are computationally powerful, and their transformations are easy [3].

General purposed artificial intelligence optimization algorithms are divided into various groups, such as biology-based, social-based, chemical-based, physics-based, music-based, mathematics-based, sports-based, swarm-based, plant-based, light-based, and water based. Their combinations can also be considered as a hybrid category. OIO and RO are the newest artificial intelligence optimization algorithms inspired by the light behaviour. OIO is inspired by the optical characteristics of convex and concave mirrors that can be used for searching the best solutions for different types of optimization and search problems. When the light rays fall on the convex mirror, they are reflected from the principal axis, and divergence occurs. When they hit a concave mirror, these rays are reflected in the direction of the principal axis, and convergence occurs. The exploration and exploitation capabilities of OIO are adjusted considering the convex and concave mirror phenomena [4, 5]. According to light refraction law of Snell, light is refracted when it passes through environments with different luminance factors. Inspired by this feature of the light in the RO, it uses the light as a candidate solution. The transition of the ray is used to obtain the optimal solutions [6].

RO was used to reduce the weight of truss under necessary constraints by Kaveh and Khayatazad in 2013 [7]. During this study, numerical results were compared for the five truss structure, and it was observed that the obtained truss weight was at a satisfactory level. RO gave better results than GA [8], ACA [9], BBBC [10], and PSO [11] algorithms. However, its performance was slightly lower than HPSACO [12], which is a hybrid method. Kaveh and his colleagues developed RO in 2013 and adopted a new approach to produce new candidate solutions that had no restrictions on the number of variables of the problem interested. That is why there was no need to group the variables in the algorithmic process of RO [13]. With this new RO developed, a better balance between the exploration and exploitation was achieved. In addition, the algorithm was improved considering transport constraints [14]. Using the RO in 2014, an effective hybrid method for the shape and size optimization of the truss structures was implemented [14]. For this hybrid developed algorithm where PSO, HS, and RO were used together [14]. In this hybrid method, PSO algorithm was used as the main engine. While the movement vector was developed by the RO, HS was used to enhance the local search skill. The experimental results of this hybrid method showed that it gives better results than the existing mathematical and artificial intelligence optimization algorithms [14].

The OIO algorithm was applied to constrained problems, namely mechanical real engineering problems by Kashan in 2015 [5]. These tests were performed with five real-world engineering problems. The performance of OIO was compared with many artificial intelligence optimization methods, such as CPSO [15], PSRE [16], RSPSO [17], IHS [18], FSA [19], and SES [20]. OIO was reported as the outperformed algorithm among others [5]. In 2015, a master thesis was presented on the development of a new method for solving combinatorial optimization problems with permutation-based solution structures using the OIO method [21]. In 2015, a master thesis was published on the design of image processing methods using OIO [22]. In 2015, the OIO algorithm was used to solve the traveling salesman problem by Badrloo and Kashan [23]. In 2015, Badrloo and Kashan used the OIO method to solve the combinatorial quadratic assignment problem [24]. In 2016, OIO algorithm was used for routing and clustering in wireless sensor networks [25]. The cluster head choice and routing problem in wireless sensor networks is a known optimization problem due to the high computational complexity of large-scale networks. In their study, OIO was adapted for cluster head choice problem considering distance, energy, and node level parameters.

The OIO based routing method was proposed to calculate the path to the base station from each cluster head, considering the same parameters, such as distance, energy, and node level. The performance evaluation of OIO was extensively evaluated and compared with other routing methods. OIO algorithm was shown to be more successful than the other techniques [25]. The conventional techniques, such as HF [26], EADC [27], and DHCR [28] were not suitable for cluster head choice and routing problems. As the size of the network increased, the performance of these conventional techniques rapidly fell. In recent studies, it was suggested that artificial intelligence method could be developed that maximizes the coverage area and distributes the nodes to minimize the number of nodes [25]. In 2016, optimal load frequency controller gains were optimized by Ozdemir and Ozturk using an OIO algorithm in a two-area power system. In this application, OIO was used to find optimal controller parameters of PID that controlled the frequency in a two-area power system [29]. The performance of the OIO for this problem was compared with the performance of the PSO and bacteria foraging optimization algorithm [30]. It was noted that OIO is better than these algorithms in terms of values of maximum blackout and settlement time. It was suggested that the optimal PID that adjusts itself could be performed to increase the practical work on the use of OIO in this way [30].

Intelligent algorithms for optimization and search for solutions for effective solution of problems of interest are proposed. One of the important current trends in the field of intelligent algorithms is the development of new search methods based on light. Concepts, events, and processes in light behaviours seem to be an inspiring guide for the development of effective optimization algorithms. This work aims to review the most important concepts of new existing two light-based intelligent optimization methods and their specific characteristics in the frame of complex optimization problems. The performances of light-based artificial intelligence optimization algorithms are also compared for the first time under equal conditions using unconstrained benchmark problems and constrained real engineering problems in this study.

2. METHODS

Nature has always been a good teacher for people. For instance, the invention of radar has been possible by the behaviour of the bats. Intelligent optimization methods inspired by the behaviour of natural beings or natural phenomena are used to solve problems that take a long time or mathematical models cannot be derived. In many problems, the solution search space is infinite or so large that all candidate solutions cannot be evaluated. For this to be acceptable, it is necessary to evaluate the solutions and find a good solution. Evaluating solutions in such a way that they are acceptable for such problems means evaluating "some solutions" in the entire solution space. The way some solutions are chosen and how they are selected varies based on artificial intelligence method [31].

The solution proposed by artificial intelligence optimization techniques for solving the problem may be perceived as good, global, or near-global optimal solution [31]. Artificial intelligence optimization algorithms are computational methods that are defined to find what is effective from various alternative actions to achieve any purpose or reach a specified goal.

Artificial intelligence optimization algorithms are categorized according to whether they are inspired by nature or not, a number of candidate solution they iterate is one or more, the objective function is dynamic or static, the memory structure is used or not, and they use single or multiple neighbourhood structures.

The reasons for the need to use artificial intelligence optimization algorithms are:

a) The optimization problem may have a structure in which the optimal solution finding process cannot be defined;

b) In terms of clarity, intelligent search algorithms can be much simpler in terms of decision makers;

c) Intelligent optimization algorithms can be used as part of the learning and precise solution finding process;

d) Definitions made using mathematical formulas often ignore the most difficult parts of real-world problems; inaccurate data used to determine model parameters can lead to greater errors than the suboptimal solution that the artificial intelligence optimization approach can produce [32].

General purposed artificial intelligence optimization algorithms are divided into various groups, such as biology-based, social-based, chemical-based, physics-based, mathematics-based, music-based, sports-based, swarm-based, plant-based, light-based, and water based. Their combinations can also be considered as hybrid category.

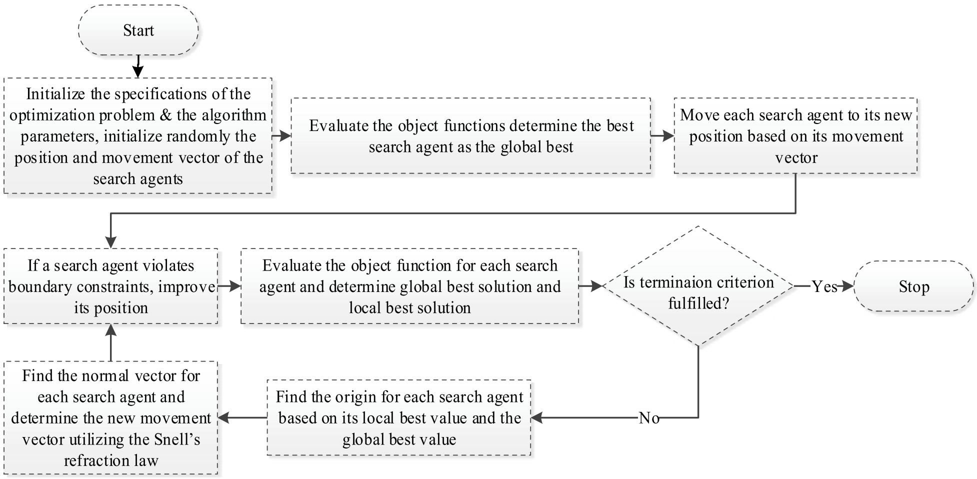

Fig. 1. The flowchart of the RO

All these population-based iterative methods follow a balance between exploitation and exploration as iterations progress. In general, exploration will be more effective in the first stages of the iteration, but exploitation will be strengthened towards the final iterations.

2.1. Ray Optimization

RO is a population-based general purposed stochastic artificial intelligence optimization and search algorithm proposed by Kaveh and Khayatazad in 2012 [6]. The light, which is also a natural event, is refracted and changes direction according to the law of refraction of light when passing from the light environment into a dark environment. Inspired by this feature of the light in the RO, it uses rays belonging to the light as a candidate solution. This behaviour of light helps to explore the search space in the first iterations, while it helps converge to the optimal solution in the last stages [6]. The optimization process ends when predetermined criteria are satisfied. If the criteria are not met, the optimization process continues, and the candidate solutions are moved to their new location. The steps are iterated until one of the defined criteria is met. The flowchart of the RO is shown in Fig. 1 [6].

2.2. Optics Inspired Optimization

OIO is a light-based physics inspired artificial intelligence optimization algorithm proposed by Kashan [4, 5]. Optics examines light properties, its behaviour, and interaction with matter. Practical applications of optics include mirrors, lenses, telescopes, microscopes, technology. The curved or spherical mirror has a curved concave or convex reflective surface. Most curved mirrors are shaped like a spherical piece.

Since the exploration and exploitation capabilities of OIO are controlled by mirror phenomena [4, 5], as described in the introduction, the reflection surface of the mirror functions as a search function. The flowchart of OIO is shown in Fig. 2.

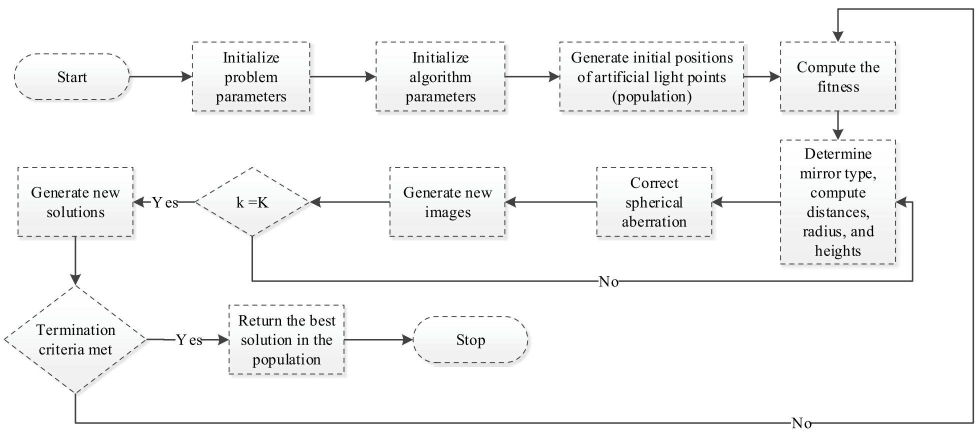

Fig. 2. The flowchart of OIO

Table 1. Algorithm Performances in Benchmark Functions

Benchmark function	Optimization algorithms				
	GEN	***GEN_S***	***GEN_S_M_LS***	***OIO***	***RO***
Griewank n=2	18838(0.91)	3111(0.91)	1652(0.99)	1825.94	1091(0.98)
Sphere n=3	9900	3040	1281	506.72	452
Goldstein and Price n=2	1478	1478	1325	1071.4	451
Exponential n=2	938	936	807	572.14	136
Exponential n=4	3237	3237	1496	1376.18	382
Exponential n=8	3237	3237	1496	2889.08	1287
Exponential n=16	8061	8061	1945	28994.14	17236(0.46)
Cosine Mixture n=4	2105	2105	1539	1673.7	802
Bohachevsky 1 n=2	3992	3356	1615	567.36	677
Bohachevsky 2 n=2	20234	3373	1636	620.7	582
Rastrigin n=2	1533(0.97)	1523(0.97)	1381	753	1013(0.98)

3. RESULTS

3.1. Results within Unconstrained Benchmark Functions

Researchers often use benchmark functions to compare the search and optimization algorithms [33]. There are many benchmark problems that are defined as unimodal, multimodal, and composite. In addition to complex mathematical expressions, the benchmark functions have many local and global minimums. Because of these features, the performance of artificial intelligence optimization algorithms is evaluated under equal conditions. In this paper, the performances of light-based intelligent search and optimization algorithms within Griewank, Cosine Mixture, Goldstein and Price, sphere, exponential, Bohachevsky1, Bohachevsky2, and Rastrigin benchmark functions were compared.

The performance comparison of OIO and RO, which are light-based optimization algorithms, is shown in Table 1 using benchmark functions. Light-based optimization algorithms are also compared with genetic algorithm and some of its variants in this table [6]. The number of function evaluations to achieve the predefined accuracy rate ($\varepsilon = f_{min} - - f_{final}$ =10–4) is listed in this Table. Values written in parentheses in Table 1 show the ratio of successful runs of the algorithms according to this predefined accuracy rate. The absence of the parentheses shows that the algorithm is successful in all runs. During the experiments, problem dimension for sphere function was defined as 3, problem dimension for the Cosine mixture function was defined as 4, and problem dimension for other functions was defined as 2. The number of populations was 20, the number of function evaluations (NFE) was 20000, and the number of independent runs was selected as 50. In addition, the performance of light-based optimization algorithms was measured by choosing the exponential test function dimension 2, 4, 8, 16 to check the performance in high problem dimensions. When the problem dimension is 16 and the population number is 100 in the exponential function, NFE is determined to be 50000 and the obtained results are listed in Table 1. In this Table, GEN, GEN_S, GEN_S_M_LS are variants of genetic algorithms whose performance has been reported promising [10].

When examined in detail in Table 1, it is seen that RO in the Griewank test function gives better results than all other artificial intelligence optimization algorithms. The OIO algorithm produced better solutions in terms of the ratio of successful runs. Light-based optimization algorithms are much more successful than other methods within sphere, Goldstein and Price, Bohachevsky 1, Bohachevsky 2, and exponential for n= 2 and n= 4. For exponential n=8, RO was seen to perform better than all other methods. However, it is impossible to generalize that the light-based methods are better than all other methods, because the OIO algorithm performed worse results in the exponential test function than the GEN_S_M_LS algorithm. It was seen that RO was the most successful method in the cosine mixture test function. However, it was that the OIO algorithm was more successful than the GEN and GEN_S algorithms, but it was observed that it

Table 2. Obtained Optimum Results from Different Methods for Tension/Compression Spring Design Problem

Method	Design variable and cost			
	x_1	x_2	x_3	f_{cost}
RO	0.051370	0.349096	11.76279	0.0126788
OIO	0.054557	0.429089	8.053812	0.0128404
Belegundu	0.050000	0.315900	14.250000	0.0128334
Arora	0.053396	0.399180	9.185400	0.0127303

was more unsuccessful than the GEN_S_M_LS algorithm. OIO seemed the best algorithm for Rastrigin function.

3.2. Results within Real-World Engineering Design Problems

The Tension/Compression Spring Design engineering design problem was first introduced by Belegundu and Arora [7]. Minimizing the weight of a tension/compression spring subjected to constraints on a minimum deflection, surge frequency, and shear stress [7] was aimed at this problem. The problem has four non-linear inequality constraints. It also has three continuous variables.

During the experiments, the number of populations was 40, NFE was 10000, and the number of independent runs was 50. The performance of light-based optimization algorithms under equal conditions were evaluated. The design variable values of the problem and the best cost values are shown in Table 2. In addition, mean values and standard deviation values obtained from the algorithms for this problem are listed in Table 3.

As shown in Table 2, RO performance is better than OIO algorithm for best results (f_{cost}). It cannot be concluded that all the light-based optimization algorithms are better than the other algorithms. Because during the experiments, OIO algorithm did not find better results than Belegundu and Arora [34]. However, as shown in Table 3, OIO gave more stable results than the RO algorithm according to the obtained standard deviation values and mean values.

The main object in welded beam engineering problem is to obtain minimum manufacturing cost of the welded beam subjected to constraints on shear stress, bulking load, bending stress, end deflection, and side constraint [7, 30, 35]. It also has four continuous variables.

During the experiments, the number of populations was 40, NFE was 10000, and the number of independent runs was 50. The performance of the light-based optimization algorithms was tested under equal conditions. The design variable values of the problem and the best cost values are shown in Table 4. In addition, obtained mean values and standard deviation values are shown in Table 5. The success of light-based optimization algorithms was compared with other mathematical optimization algorithms.

Table 3. Mean and Standard Deviation Values for Tension/Compression Spring Design

Method	Mean and standard deviation	
	f_{mean}	*Std. dev.*
RO	0.13547	0.001159
OIO	0.01326	0.000297

As shown in Table 4 and Table 5, RO was more successful than OIO algorithm in terms of best cost result and mean cost result, respectively. Table 5 shows that light-based optimization algorithms are much more successful than other methods such as Approx, David, Simplex, and Random [35]. As shown in Table 4, light-based optimization algorithms were experimentally demonstrated that they are less fitted to the local minimum and better converged to the global minimum than other methods used in testing in real-world engineering problems.

4. DISCUSSION

For real world optimization problems, there are many intelligent methods that have been inspired by nature or other phenomenon. Almost all of the intelligent optimization algorithms perform with metaheuristic population-based search procedures that incorporate random selection and variation. These algorithms should have two key components: exploration and exploitation.

RO and OIO are two of the methods inspired by the concepts, events, and processes in light behaviours, and they are entitled as light-based in-

Table 4. Optimum Results for Welded Beam

Method	Design variable and cost				
	x_1	x_2	x_3	x_4	f_{cost}
RO	0.2037	3.5285	9.0042	0.2072	1.7353
OIO	0.1914	3.8049	9.1382	0.2052	1.7605
Approx	0.2444	6.2189	8.2915	0.2444	2.3815
David	0.2434	6.2552	8.2915	0.2444	2.3841
Simplex	0.2792	5.6256	7.7512	0.2796	2.5307
Random	0.4575	4.7313	5.0853	0.6600	4.1185

Table 5. Mean and Standard Deviation for Welded Beam

Method	Mean and standard deviation	
	f_{cost}	*Std Dev*
RO	1.9083	0.173744
OIO	2.0381	0.167309

telligent optimization algorithms in this paper. According to the experimental results obtained, RO algorithm seems better than OIO in both unconstrained benchmark test functions results and constrained real-world engineering problems. However, it is not the best algorithm when compared the other methods. According to the No-Free-Lunch theorem, there is no single universally most efficient method for every types of optimization problem. Though theoretically solid, No-Free-Lunch theorem may have limited impact in practice because solving all problems and taking average performance are not needed. One of the main targets of optimization problems in practice is to inquire to obtain high-quality possible or optimal solution in an acceptable duration. For some types of problem, some methods can outperform the others. Furthermore, balance between exploration and exploitation is needed so that a method can achieve good performance. However, obtain such a balance is not resolved. No method claims that such a balance has been achieved. This balancing is a hyper optimization problem that depends on many factors, such as the working mechanism of a method, its parameter settings, controlling of these parameters. Furthermore, such balance may not universally exist, and it may depend on the interested problem.

Researchers do not aim to develop a single most successful method to solve all types of problems. They intend to propose more successful versions of the methods and more new methods based on untested phenomena in the nature. Furthermore, values of parameters of the algorithms affect the performance. Setting the right fine-tuned values is essential for better performance. Setting parameters is still an active research area.

4. CONCLUSIONS

Light-based optimization methods and literature reviews based on these algorithms were compiled for the first time in this study. The performances of these algorithms were tested using unconstrained benchmark functions and constrained real-world engineering problems. Light-based optimization algorithms were also compared with other intelligent search and optimization methods, such as GA and its variants. The success of light-based optimization algorithms was experimentally proven.

The performance of light-based optimization algorithms in constrained real-world engineering problems was evaluated. During these tests, welded beam problem and tension/compression spring design problem were used. The performances of light-based optimization algorithms were compared for the first time under equal conditions. In the tension/compression spring design problem, RO outperformed all other methods, including the OIO algorithm. However, in this problem, the OIO algorithm could not obtain better results than other methods. In this context, all the light-based optimization algorithms did not yield better results than the other artificial intelligence methods in the literature within the problem of the tension/compression spring design. In the welded beam problem, it was seen that the light-based optimization and search methods better converged to the global minimum than the other methods. Another important consequence of this is that an artificial intelligence method that yields good results in a constrained real engineering problem cannot be proven to yield good results in all other constrained and unconstrained problems and functions.

To the best of our knowledge, there is not any light-based artificial intelligence optimization algorithm developed in the literature other than the RO and OIO algorithms. In terms of performance of light-based optimization algorithms, RO algorithm, when both unconstrained benchmark test functions result and constrained real-world engineering problems tests are taken into consideration, usually converges better to the global solution. Light-based optimization algorithms are very new, and the obtained results are based on their classical main versions. In future works, better results can be obtained by proposing new distributed, hybrid, adaptive, and parallel versions using optimized parameters. Chaos theory and quantum computing features and capabilities can also be built into these methods to improve performance.

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