The Analysis of Chaos-Based Metaheuristic Methods

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The concept of chaos has been applied extensively in various applications with the growth of nonlinear dynamical systems that are highly sensitive to the initial state. Chaos-based algorithms can generate a large number of different search points in a short time, which can help explore the optimization area more efficiently and quickly than traditional optimization algorithms. In this regard, a new method named CSCSO is proposed to improve the shortcomings of the recently proposed Sand Cat Swarm Optimization (SCSO) algorithm with this chaos theory. This algorithm has also been tested in engineering and social science-based constrained problems. Especially in social sciences, it solves basic problems with this kind of artificial intelligence-based mechanism instead of traditional methods such as questionnaires and fieldresearch.

Chaotic Sand Cat Swarm Optimization | chaotic maps | constrained problems | hybrid metaheuristics | multidisciplinary problems

1. Introduction

In general, the most common and economical process for finding the best value (minimum or maximum) in systems and problems with challenging design is optimization [1][2]. As the size of the problem increases, so does its complexity, and therefore it becomes more difficult to solve [3]. Similar problems are called Nondeterministic Polynomial time (NP-hard) problems [4]. Such problems are common in real-world problems that have various objectives and constraints. Metaheuristic algorithms are the most popular and efficient of the different approaches to solving such problems. These algorithms can be efficient in solving nonlinear and non−differentiable design problems. These algorithms are stochastic-based optimization methods that prove their adequacy to solve many design problems in different fields [5]. Therefore, it is possible to develop different algorithms for various problems. Moreover, according to the No Free Lunch (NFL) [6] theorem, not every algorithm can best solve all problems, so it is important to build up new algorithms.

It will be helpful to briefly examine the properties of metaheuristic algorithms for the motivation of the study and the explanation of the main issue. The metaheuristic algorithms consist of two important phases: exploration and exploitation [7]. In the exploration phase, it provides numerous population-based parameters to explore the search space. In the second stage, it is tried to obtain the optimum solution from the existing search space, which can be global or local. Slow convergence and high computation time are unacceptable, although it is by nature not to reach a one-step solution. In these phases, search agents try to seek solutions and catch what they find. In this behavior circulation, the most critical issue is that the processes in these two phases and the transitions between phases are balanced. However, it should be noted that some algorithms can be unstable, converge slowly, and fail to go outside the local sometimes or in some problems. In this case, new strategies can be proposed to solve these limitations and/or improve the performance of current algorithms. Examples of these strategies are parameter tuning, elitism, chaos, and hybrid strategies [5][8]. The concept of chaos, which is one of the most effective approaches, and this strategy is planned to be used in the Sand Cat Swarm Optimization (SCSO) algorithm [9]. The performance of this algorithm is degraded by some complex and constrained multidisciplinary problems. Moreover, transitions between exploration and exploitation in the SCSO are sometimes slow; based on this, there may be slow convergence. Briefly, the main gaps of the SCSO algorithm are sometimes the problems of low search consistency, local optimum trap, inefficiency search, and low population diversity. Accordingly, it is planned to eliminate these problems with a chaos strategy. The concept of chaos has been applied extensively in various applications with the growth of nonlinear dynamical systems that are highly sensitive to the initial state. Chaos-based algorithms can generate a large number of different search points in a short time, which can help explore the optimization area more efficiently and quickly than traditional optimization algorithms.

Metaheuristic algorithms try to be effective in various engineering optimization processes by using chaotic maps based on the concept of chaos with random and regular features. According to [10][11], as the initial population diversity increases, it becomes possible for the algorithm to escape from the local optimum trap and prevent premature convergence. On the other hand, in another study [12], it was found that the application of the chaotic component in optimization is a performance-enhancing factor in many algorithms.

2. The Analysis of Chaos-Based Metaheuristic Methods

The metaheuristic algorithms are broadly divided into four main categories: evolutionary, physics-based, human behavior, and swarm intelligence algorithms [3]. It is worth noting that there are also hybrid methods consisting of these four main categories. In evolution-based algorithms, the biological behavior of different systems is taken into account. One of the famous algorithms in this category is the Genetic Algorithm (GA) [13]; it is based on Darwin's theory. Among the studies in this category, Refs. [14][15][16] are recent studies that can be given as examples. Physics-based algorithms are the category that exhibits random behavior inspired by the laws of physics in nature. Some of the studies in this category are presented in [17][18][19]. Algorithms in the third category are those inspired by the social behavior of humans. Some studies can be cited as examples in this category [20][21][22]. This category is expected to become widespread by incorporating more and more social sciences in the future [3]. In particular, it should be emphasized that there are multivariate dynamic problems in social sciences, and in solving these problems, these algorithms expected to be used frequently, such as artificial intelligence and machine learning [23]. The last category is Swarm Intelligence (SI) algorithms, which have received a lot of attention recently by researchers. The SI is also defined as the collective behavior of a decentralized or self−organizing system [24]. This approach consists of a large number of members with limited intelligence who interact with each other based on simple principles. Many studies have been performed in this category [24][25][26][27]. The hybrid algorithms can be presented for more efficient solutions to some global and/or specific problems. Considering that there are difficult and complex problems faced in our real world, it is inevitable that such algorithms will become widespread. In accordance with this purpose, they are looking for better solutions by combining the pros of the metaheuristic algorithms under consideration. Hybrid methods generally either present different existing metaheuristic algorithms as a single new algorithm or make improvements to existing algorithms. Recently, out−of−the−box hybrid models realize the concept of chaos by adapting them to metaheuristic algorithms. Some examples are listed in [28][29][30]. A generalized version of these classifications is presented in **Figure 1**. Its wide-ranging metaheuristic approach is used today for a variety of real problems, ranging from engineering to intelligent systems [31][32][33][34][35]. More examples of studies in these categories [36][37][38][39][40][41][42][43][44][45][46][47][48][49][50][51][52][53][54][55][56][57] are referred to in this figure.

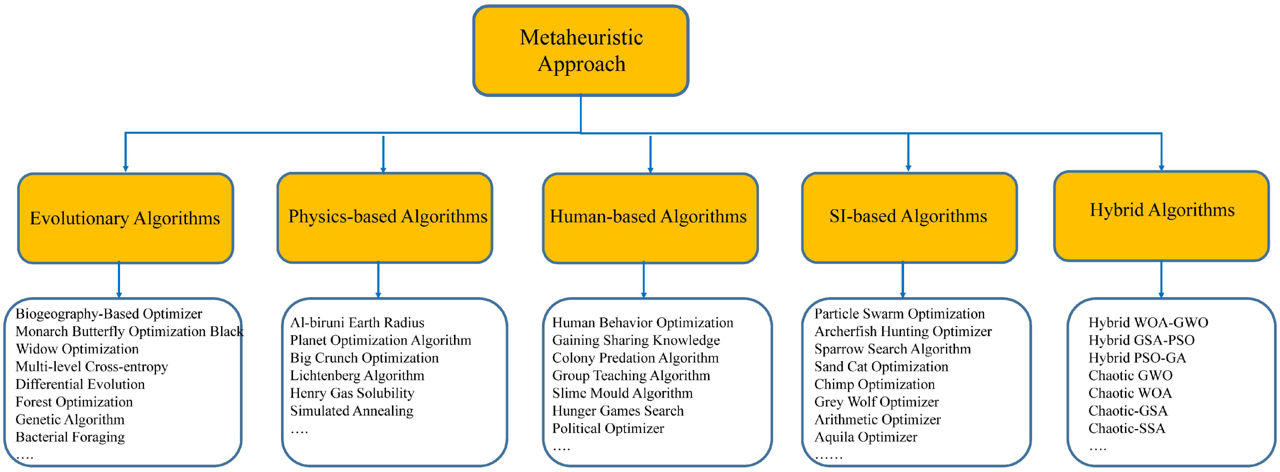

Figure 1. Generalized classification of metaheuristic algorithms [3][13][14][15][16][17][18][19][20][21][22][23][24][25][26][27][28][29][30][31][32][33][34][35][36][37][38][39][40][41][42][43][44][45][46][47][48][49][50][51][52][53][54][55][56][57].

In [58], a hybrid chaos-based algorithm was proposed, called Broyden–Fletcher–Goldfarb–Shanno algorithm (Chaos−BFGS). BFGS is a quasi−Newton method for local optimization devised. Methods based on Newton's model have a fast convergence rate and high efficiency, while optimization results are based on selected initial points. The authors introduced pseudo-randomness and disorder by adding chaotic behavior to the relevant algorithm. In [59], researchers proposed a new metaheuristic based on chaotic strategies to improve the performance of power distribution systems. In this algorithm, called Modified Symbiotic Organisms Search (MSOS), they tried to solve the constraints of the economic dispatch system of the relevant system. In this study, they helped the algorithm to find a global optimum solution with a superior convergence rate by applying different logistic chaos maps. Similarly, in [60], the researchers were able to significantly improve the performance of the Big Bang–Big Crunch (BBBC) [61] algorithm with three different chaos maps and five unique chaotic-based strategies.

In [62], the author tried to improve the performance of the Cuckoo Search Algorithm (CSA) by incorporating ten chaotic maps. They claimed to improve the performance of their algorithm in terms of quality solutions and convergence behaviors, based on their results in 27 benchmarking problems. In another study [28], ten specialized chaotic maps were applied to the Grey Wolf Optimization (GWO) algorithm. The authors claim that the algorithm they propose has acceptable performance in the global optimum finding and convergence rate for constrained problems, based on their results. In this regard, the results were compared with the standard GWO. In a study [63], the authors used augmenting chaotic maps for improving the performance of the Krill Herd Optimizer (KHO) [64] in terms of computational time and convergence rate. This conclusion was reached after encountering the standard KHO and a few other algorithms. In another study [65], chaos theory was used to find the local optimum solution and solve slow convergence problems of the GA. In this study, the proposed chaotic GA demonstrated successful performance in the optimum design of critical hydroelectric systems.

In another study [66], the failure of the Dolphin Swarm Algorithm (DSA) [67] in some cases, such as incomplete solution and entrapment in local optima, was discussed. To solve these problems, the authors augmented eight chaotic logistic maps. Their outcomes have shown a significant improvement. The authors claim that their proposed algorithm achieved improvements in the convergence rate, along with the elimination of the above problems, by comparing their results with the standard DSA. The Chaos Ant Colony Algorithm (CACA) was proposed in [68]. In this study, efficient tool path, motion, and handling were estimated. The results show that pocket milling can be optimized with effective tool trajectories with the help of CACA.

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