Comparison of bioinspired computation and optimization techniques

Muhammad Kashif Hanif, Ramzan Talib*, Muhammad Awais, Muhammad Yahya Saeed and Umer Sarwar

Department of Computer Science, Government College University, Faisalabad 38000, Pakistan

In this article we focus on the bioinspired algorithms and their computational classification. The basic ideas and various techniques developed recently are described. The research outcomes in the computational area of solution optimization are presented for different problems, i.e. mathematical, combinatorial, exact approximation and multiple objective optimization. Moreover, evolutionary, stochastic and swarm optimization algorithms are discussed. All these areas have principles of extracting natural concepts in the form of mathematics and algorithms. Nature-inspired algorithms can help explore new dimensions to solve many problems with optimal cost and time. This review shows that bioinspired computing can provide innovative optimal computational algorithms.

Keywords: Bioinspired computing, combinatorial optimization, computational complexity, evolutionary algorithms.

NATURE has been a source of motivation for humans in solving problems for centuries. Natural concepts are remarkably dynamic, universally diverse and robust. Motivation from natural science has steered towards development of a number of fruitful algorithmic methodologies. Various problems arising in different fields require combinatorial optimization[1].

Traditional problem-solving techniques can be classified into exact mathematics and heuristics. Sometimes, exact mathematical solutions have high computational complexity. Thus, it will be difficult to solve problems in an efficient manner. In this situation, heuristic approach is the best alternative. It can be used to solve the multifarious issues and difficult problems[2].

Bioinspired computing (BIC) can help provide efficient, flexible and multifarious computational algorithms. In recent years, bioinspired algorithms have been used to solve problems in various fields. BIC solution requires choosing the suitable dimensions of the problem, evaluating the eminence of the comparative solutions and defining the operators. BIC procedures are under research for solving complex computational complex problems. These are continuously refined to be applied at a broader perspective[3].

BIC is capable of providing optimal solutions by maintaining natural balance in components of a given problem. Self-balancing characteristic is the best feature of BIC algorithms. Major elements to understand in this field are nature as a creator and inventor, environment as a field, and biological elements as computational machines having groups of algorithm. However, the practical success of these algorithms is still under study. The main reason is the randomness of these algorithms in the process of decision-making. This randomness gives rise to complexity in the process execution and understanding during implementation of BIC algorithms[1–3].

This article reviews the following optimization techniques: Mathematical optimization and combinatorial Optimization (MOCO); Computational complexity (CC); Exact optimization and approximation (EOA); Multiple-objective optimization (MOO); Evolutionary algorithm (EA); Stochastic algorithm (SA) and Swarm optimization algorithm.

Challenges to BIC

The major challenges with BIC are[3,4]:

1. To find some real model of any biological phenomena.
2. To define architectural-level processes for the identification of biological objects.
3. To simulate the fitness point, except some of artificially defined functions or the artificial fitness units.
4. To develop models that allow the resulting consequences to be able to attach themselves with the desired phenomena.

BIC optimization techniques and current practices

MOCO is used to solve certain issues of the CO like finding the shortest possible path between two cities or making the plan of an on-line exam on a network. Kurdi *et al.*[4] worked on the CO-related algorithms for multiple services of the cloud composition. They measured the

*For correspondence. (e-mail: Ramzan.Talib@gcuf.edu.pk)

complexity of algorithms using comparative situations. They classified CO into two categories. The first category consists of problems of continuous nature involving continuous variables like production lines, recursive working of machines, etc. Secondly, they discussed issues of cloud computing with dynamic parameters[4]. Amiri and Amiri[5] designed a BIC simulator which suppresses the hyper-synchronized neural cortical network. The complicated problems are conventionally solvable by calculation using derivatives or linear programming. Cordone and Lulli[6] studied the multimode control of combinatorial optimization issues. CO problems can decrease or increase certain objective functions according to a set of constraints, e.g. if path is to be detected in the shortest possible way in minimum calculations or measures required to plan for applications from the existing range of machines, etc.

CC relates exponential dimensions of the given problem to its proposed solution. It carefully studies the description of problem space in contrast to the problem dimensions. In some situations, it also relates the time exponential dimensions to the problem. Raja *et al.*[7] described the importance of bioinspired intelligence design for computational techniques in solving steady and thin flow of JS fluid over a vertical cylinder in drainage-related problems. The performance measure algorithms require the time component to provide the final answer. These assessments and analyses need to express time in all basic activities, including comparison or branching instructions, etc.[7].

EOA is applicable in situations where the optimization problem requires more accurate decisions in polynomial time. It is desirable to have a good approximation for the optimal solution. An *et al.*[8] worked on structural optimization regarding the multiple structure and payload cases. They used the two-level multipoint approximation method. Moreover, they assessed the quality and compared it with the general and specific algorithms of CO problems. Many researchers are working on the approximation algorithms to solve various issues and to improve the performance. The approximation and exact optimization are similar. Approximation theory becomes realistic in estimation process. Algorithms which have the expected approximated efficiency are generally preferred. It creates decision confidence level relating to all cases of the problems in which these algorithms need to be implemented[8].

MOO is multi-objective for related attributes and is currently being utilized for the functional objectives. It determines the priorities for the focused solutions. Yi and Sjoden[9] worked on the heuristics for optimization regarding group structures. They utilized the fitness approximation to improve the polynomial fitness evaluation goal and addressed computational challenges. This optimization technique is preferable for minimum weight targeted functions. MOO is difficult compared to single objective optimization[9]. Dullinger and Struck[10] tested the simulation-oriented MOO regarding train-tracing systems. BIC algorithms are effective for single as well as multi-objective optimizations.

SA is a set of modules which are problem independent for the designing solutions. Vitayasak and Pongcharoen[11] studied the tools regarding stochastic solution using dynamic approach. They classified problems with refernce to the stochastic demand using genetic algorithms and pre- or post-modified algorithms of backtracking search. Stochastic search algorithms are general-purpose algorithms contrary to the previously designed classical approach algorithms which target the runtime or quality of the approximation. Selection of stochastic search algorithms depends on previously developed and analysed classical algorithms. Sundar and Michael[12] worked on surrogate enhanced algorithm of stochastic nature and identified functions regarding the analysis of reliability.

EA depends on natural processes of evolution and solves problems by creating sets of reference points relating to the positive results obtained. Li *et al.*[13] studied multi-objective algorithms based on evolutionary approach in hyper heuristics method for the layouts of wind farms and their optimization. These optimizations are applicable where the real programs need optimization with their actual form of functioning and are generally not known before hand. The values reduction process for the evaluation functions is repeated until a satisfactory result is obtained.

Jothi *et al.*[14] analysed minimum cost-matching problems on the minimum spanning tree-dependent neighbourhood graph. They studied functional division of groups for the similar and closely related genes using eigen analysis. Shalom *et al.*[15] generated maximum matching online completeness graphs for optical networks. They proved that minimum cost problems are solvable in polynomial time. Zhang *et al.*[16] generated combinatorial test suite using combinatorial optimization.

BIC has been used in different applications. Zhao and Wang[17] designed BIC algorithms for scheduling gasoline blending. Zheng and Jiang[18] designed the organic electronics for BIC-coplanar (gate-coupled) and ITO-free transistors employing nontoxic biopolymer natural electrolyte. Šešum-Čavić *et al.*[19] studied search-based BIC algorithms with regard to P2P unstructured overlay networks for evolutionary computation. Maitra *et al.*[20] studied AI algorithms for autonomous landing. Dou and Dvan[21] explored LFB pigeon-inspired and control optimization parameters in automatic system of carrier landing. Konar and Bhattacharyya[22] studied hybrid-improved quantum-inspired algorithm for CPU scheduling for real-time tasking in current multiprocessor system. Ahmad *et al.*[23] discussed BIC-based detection and mitigation for management of data in social ad-hoc networks. Samanta and Choudhury[24] suggested evolutionary quantum-inspired algorithm for scaling of the optimization factor in embedding medical information. Jia *et al.*[25] explored the control for joint topology and BIC multi-radio routing model. Sen and Kankanhalli[26] performed image processing and presented salience model center-surround computation. These examples show the diversity of BIC algorithms being used in different areas.

Swarm intelligence (SI) has attracted the attention of researchers in all fields. Bonabeau *et al.*[27] defined SI as 'The emergent collective intelligence of groups of simple agents'. SI is the combined intelligence performance of decentralized and self-organized systems of simple agents. It includes insects, nest-building of birds and co-operative transportation. Two primary conceptions that are considered essential for SI are default organization of its parameters and rationale division of labour. Self-organization of these algorithms can be defined as the potential of any system to engage its components into an appropriate structure without requiring any external help. Self-organization property depends on four properties, i.e. positive feedback, negative feedback, fluctuations and multiple interactions. Feedbacks are helpful for strengthening and stabilization, whereas fluctuations are valuable for the randomness. Multiple interactions take place while the swarms divide information amongst themselves in their searching area. Researchers define division of labour as the synchronized execution of a variety of simple and realistic tasks. These divisions allow the swarms to embark upon multifarious problems that involve group of professionals and common workers[27].

Ant colony optimization (ACO) is a nature-based approach for solving optimization problems. EA solutions are based on the existing and currently available solutions. Randomized layering is used in the construction of a new ACO solution and directed graphs have the capability to represent it. ACO algorithms are developed over the common principles of ant behaviour to seek sources of food in all directions. It is interesting to note that ants always search for food in a quick manner. They do this by the shortest possible path towards an identified food source. Information relating to path selection to access the desired food is actually divided into the ant's leaves. This path is selected in intelligent manner. It takes relatively more time for multi-source food. Ismkhan[28] studied the effectiveness of heuristics approach regarding ant colonies and optimization for handling large-scale entities management. Biologically encouraged processes like AC algorithm for optimization have several applications in logistics, engineering, etc.[28].

Artificial bee colony (ABC) is inspired by the rational behaviour of honey bees. It is based on general controlled and estimated parameters like size of the colony, maximum cycle number, etc. ABC is a tool which provides group-based search techniques for issues like finding food, changing position, etc. Moreover, bees target important food points as ranked spots. Luo and Liu[29] studied the ABC algorithm and targeted optimizations having multi-objective functions.

Bacterial foraging optimization algorithm has become increasingly popular in scientific and engineering fields in recent years. This algorithm thoroughly investigates the solution space. It finds a global or almost global optimal solution in a short time. Traditional methods of optimization have many limitations in the development of a mathematical model and the investigation of operations. Furthermore, traditional algorithms have no general solution strategies that may help in solving the problem of different variables and constraints[30].

Cat swarm optimization (CSO) is based on the behaviour of cats. The CSO algorithm and its variants have been implemented for various optimization tasks. Certain variations of the algorithm exists, which had been developed by various researchers[31].

Cuckoo search (CS) is one of the intelligent swarm algorithms. Since its introduction in 2009, there have been significant changes to it. CS offers many advantages due to its simplicity and efficiency in the solution of nonlinear optimization problems with real engineering applications[32].

Fast bacterial swarm algorithm is a powerful optimization function. Moreover, the bacterial feeding algorithm has been introduced on the principle of the flock of birds mechanism. It has the advantages of two bio algorithms to improve convergence and functional optimization. It provides a new parameter like the attraction factor that allows adjusting the trajectory depending on the location. To increase the ability of the local search, the adaptive step length is used. The algorithm evaluations showed a fast convergence capability and improved optimization accuracy[33].

Firefly algorithm (FA) is a latest method inspired by nature. It is a meta-heuristic algorithm used to solve complex optimization problems. It analyses the effect of changing certain parameters related to optimization problems. FA determines the distance between points to obtain the optimal solution. It is a source to analyse the distances between convergence points as well as with other related functions utilizing the attractiveness concepts of fireflies[34].

Artificial fish swarm algorithm has been developed to solve the combinatorial optimization problem. The aim is to minimize the time regarding turnover of ships over the container terminals to increase the efficiency, and ease and satisfaction. Experimentation over the years has proved its efficacy and feasibility with the rational parameters. It has better convergence and performance compared to the other genetic algorithms[35].

Flower pollination algorithm (FPA) is the most advanced natural algorithm based on the process of plant pollination. This optimization keeps improving productivity and efficiency by reducing costs. It is important to make a solution optimal for valuable resources under conditions with different limitations. FPA is a reasonable choice in such cases[36].

Summary

This study provides a comprehensive overview on bio-inspired computing in the perspective of combinatorial optimization. It discusses the bioinspired methods of stochastic nature and presents the related work carried out during the last few years. BIC algorithms have characteristics of self-correction, enhancement and are naturally equipped to respond to the continuous changing environments. This study urges researchers to examine the characteristics of real-life environment to find the optimal natural strategies. Scientists can realize the existence of natural algorithms in the surroundings, e.g. interaction of the species ranging from bacteria to humans, algorithms of balanced ecosystems, diversity of structures like rainfall, forests, clouds, etc. Researchers can translate mysteries of the environment in the form of algorithms to use them in computational technology. This article provides an analysis of state-of-the-art events over the past years, including a discussion of the theoretical foundations and research areas for further development of BIC algorithms.

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