An Understanding of Artificial Bee Colony Algorithm from the Perspective of Computation and Applied Mathematics: A Comparative Study

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Abstract--In the recent past, one of the swarm-based algorithms that have been introduced is Artificial Bee Colony (ABC) algorithms. The role of ABC lies in the stimulation of honeybee swarms' intelligent foraging behavior. This study applied the ABC algorithm toward large numerical test function optimization. Also, the results were compared with those that had been reported by experimental studies employing evolution strategies, differential evolution algorithm, particle swarm optimization algorithm, and genetic algorithm. From the findings, the study established that ABC exhibits superior performance compared to population-based algorithms, with other situations also witnessing the algorithm’s performance likened to or similar to the population-based algorithms. The factor that explained the superiority of the ABC algorithm was that it employs fewer control parameters.

1. Introduction

Given difficult optimization problems, near-optimal solutions have been achieved by population-based optimization algorithms [1]. Specifically, nature motivates or inspired these algorithms. For the population-based algorithms, a common factor is that they modify populations with potential solutions to target problems via the application of operators on solutions relative to their fitness information [2]. As such, they move the population toward solution areas that are deemed to be better placed within the search spaces [3]. The two broad categories of population-based optimization algorithms include swarm intelligence-based algorithms and evolutionary algorithms [4, 5]. In this paper, the central purpose was to offer a comprehensive comparative study examining swarm-based and renowned evolutionary algorithms in relation to large numerical function set optimization. To achieve the intended aim, the study summarized the functionality of other population-based algorithms before examining real bees’ foraging behavior, with the investigation culminating into ABC algorithm simulation of the real bees’ behavior and comparing the results with the performance of other algorithms – relative to their ability to optimize large numerical function sets.

2. Methodology – Experimental setup comparing ABC with PSO, DE, and GA algorithms

One of the factors that were considered in the experimental setting was that for each algorithm, common parameter values were set to be the same. Some of these common parameters included the total evaluation number and the population size. Specifically, the study chose 50 as the population size. For all functions, the study also settled on 500,000 as the maximum evaluation number. For the GA algorithm, a binary standard GA was employed and it had elite units, mutation, crossover, random selection, seeded selection, fitness scaling, and evaluation. Also, the rate of 0.8 was employed relative to single point crossover. Furthermore, 0.01 was selected as the experiment’s mutation rate, with the selection method implemented in the form of stochastic uniform sampling technique. The value of the
generation gap was also set at 0.9 and it represented the proportion of the population that was worth replacing.

In relation to the settings of the DE algorithm, the real constant was selected as F and it was poised to affect differential variations between two solutions. The value of F was set to 0.50. Furthermore, 0.90 was the crossover rate value and it was projected to control the population’s diversity change. Lastly, the settings for the PSO algorithm were set in such a way that the constants employed to determine or alter the weighting between population and personal experience included social and cognitive components. Indeed, both components were set to 1.80. Lastly, 0.60 was selected as the value of inertia weight, whose role lay in the determination of the extent to which the previous velocity was likely to affect the next iteration’s velocity.

In relation to the main algorithm that was under investigation, which involves ABC, the basic algorithm that was used (other than the maximum evaluation number and the population number) was that which employed the limit as the only control parameter. As such, there was no exploitation of a food source. A central assumption was that upon exceeding the limit for the source, it (the source) would be abandoned. The eventuality was that if the trial number exceeded that value of the limit, the resultant solution would not be improved anymore. To determine the value of the limit, the colony size and the problem dimension were used. The relation translated into:

\[ \text{Limit} = (SN*D) \]

In this case, D represented the problem’s dimension. On the other hand, the number of employed bees or food sources was represented by SN.

Benchmark functions were also defined. The aim was to discern specific forms of problems where the ABC algorithm was likely to exhibit superior or better performance. In so doing, the study would characterize the problem types to which the algorithm would prove more suitable for application. Therefore, the study identified 50 benchmark problems to examine how the performance of ABC algorithm would compare with that of PSO, DE, and GA algorithms. Some of the benchmark problems that were identified in the comparative study included: formulation, initial range, non-separable and multidimensional, separable, irregular, regular, multimodal, and uni-modal problems. Of importance to note is that the study selected multimodal functions to discern the extent to which the algorithms would get rid of local minima. Should the algorithm get stuck at the local minima due to poor exploration process, it would be inferred that it could not search the entire search space effectively.

3. Results and Discussion

To offer a comprehensive comparative analysis, the respective experiments were repeated up to 30 times. As they were repeated, different mean best values arising from the algorithms were recorded, having applied different random seeds. For clear comparisons, some values were assumed to be 0. Particularly, values that were considered to be 0 were those below 10-12. For pairs of algorithms, t-tests were also conducted to determine the significance between each algorithm’s results, with p-values for the respective functions also calculated. From the specific results, functions that lay on flat surfaces had all algorithms exhibit equal performance. Some of these functions included Matyas and Stepint. It is also notable that out of 50 benchmark functions that were selected, ABC and GA algorithms did not exhibit significant differences on 20 functions but ABC exhibited superior performance than GA on 28 functions. On the other hand, GA proved superior to ABC on 2 functions.

When Beale function was examined with the vicinity of minimum’s curving shape on the focus, there was equal performance in all algorithms. However, only the PSO algorithm yielded the minimum when Colville function was considered. The highest performance was also reported for the case of the ABC algorithm when there was an extension of Rosenbrock function to 30 parameters. Additional results saw DE and ABC exhibit equal performance in relation to non-symmetrical Langerman functions. However, the DE algorithm yielded the best performance for 10 and 5-parameter cases. It was also evident that as the number of variables increases, ABC’s efficiency becomes much clearer. Given 14 functions, with each function having 30 variables, results saw ABC outperforming GA on 14, PSO on 8, and DE on 6. Whereas DE was unsuccessful on 9 multimodal functions, DE and ABC were unsuccessful on 4 uni-modal functions, which included Dixon-Price, Rosenbrock, Quartic, and Colville
for DE and Quartic, Powell, Zakharov, and Colville for ABC. Also, ABS proved unsuccessful on 5 multimodal functions. However, the experimental results saw ABC emerge as the most robust and more successful algorithm on multimodal functions – compared to the performance of GA, PSO, and DE.

4. Conclusion

In summary, the main aim of this study was to compare the performance of the ABC algorithm with those of other optimization algorithms such as ES, DE, PSO, and GA. Whereas the recent past trends have seen improved versions of PSO, DE and GA evolve, this study focused on the algorithms’ standard versions. It is also notable that the integration of useful heuristics could improve the performance of the ABC algorithm but this investigation strived to compare the ABC standard version’s performance in relation to the performance of the other algorithms’ standard versions, a decision that source to achieve outcome validity and reliability – by relying or focusing on the target algorithms’ standard versions. From the findings, the study concluded that ABC algorithm’s performance is similar to or better than the remainder of the optimization algorithms, yet it uses less control parameters. The implication for the field of computation and applied mathematics is that the study’s findings were informative because they pointed to the criticality of using the ABC algorithm efficiently to solve multi-dimensional and multimodal optimization problems.

5. References

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