An efficient hybrid genetic–cuckoo search algorithm for the quadratic assignment problem

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ABSTRACT

Quadratic assignment problem (QAP) is one of the most difficult NP-hard combinatorial optimization problems with applications ranging from facility layout design, scheduling and manufacturing systems to software optimization. This paper introduces a hybrid metaheuristic algorithm based on genetic algorithm (GA) and cuckoo search (CS); an improved solution quality and convergence speed is observed for QAP instances where GA itself performs poorly as well. This approach leverages the exploration capabilities of GA with computationally intensive exploitation that is easy for CS, to create a balanced yet robust searching mechanism across complex optimization landscapes. We tested the algorithm on benchmark instances taken from quadratic assignment problem library (QAPLIB) and compared it with many classical heuristics such as standard GA, particle swarm optimization (PSO) method and original CS algorithm. Experimental findings showcase that the presented hybrid GA-CS algorithm outperforms traditional standalone GAs regarding solution quality and computational time with significance by promptly converging toward high-quality solutions, especially for medium- to large-scale test instances. In addition, performance improvements over competing methods are shown as statistically significant using the Wilcoxon signed-rank test. The results show that the proposed hybrid framework is an efficient and accurate optimization technique for solving challenging QAP.

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1. INTRODUCTION

First, we will analyze the issue introduced by Koopmans and Beckmann [1], referred to as the quadratic assignment problem (QAP). This problem is acknowledged as one of the most complex NP-hard combinatorial optimization challenges. The primary objective is to determine an arrangement of a set of facilities for a specified set of points that minimizes the flow between facilities while concurrently minimizing the distances among locations. The real examples of QAP are many: design for the layout of facilities, logistics and transportation planning, scheduling, and network design; in very large-scale integrated (VLSI) circuit placement [2]. But because it grows extremely rapidly with size due to the quadratic cost structure and combinatorial explosion from all possible assignments into two sets of points it becomes increasingly difficult, if not impossible, to apply these exact optimization methods as problems increase in size beyond a certain threshold [3]. Besides the typical uses of plant design, the QAP model has also been used in several new technical domains such as VLSI circuit placement; allocation of resources without moving a large machine that does this simply because it was designed for one type and requires another; and task mapping in distributed and IOT-based architectures. QAP efficient optimization methods are therefore important for improving design level, system efficiency of computation, and hardware resource exploitation in these environments.

Numerous studies have proposed hybrid and local search strategies aimed at improving solution quality for the QAP by intensifying promising regions within the search space [4], [5]. One reason for this is that it can return to a solution in a reasonable time but at lower cost. Meta-heuristic optimization algorithms, such as genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and cuckoo search (CS), have unleashed formidable power to cope with complicated landscapes of optimization problems [6]–[12]. While GA is quite effective at exploration of the search space with its crossover operator and mutation operator that maintain species diversity in a population, it might prematurely converge since diversity declines over iterations [13]. On the other hand, local exploitation and intensification are the emphasis of swarm intelligence algorithms, which refine potential candidate solutions but may lead to insufficient global exploration if used alone [14].

Usually, the secret in your hands to design a clearly computationally efficient metaheuristic optimization algorithm is how well you can balance between exploration and exploitation during searching process. Exploration enables the algorithm to explore different areas of search space and avoid premature stagnation, while exploitation aims at applying intensive improvement on good candidate solutions in local regions. Both mechanisms are crucial in creating successful optimization strategies, especially for complicated combinatorial problems like the QAP. Too much exploration can slow down the convergence speed, while too much exploitation may cause the algorithm to fall into local optimums. Consequently, hybrid optimization methods that combine complementary search approaches are paramount to alleviate these limitations. Nonetheless, creating a successful hybrid structure that can balance global exploration and local refinement while not sacrificing computational efficiency is still an open research question.

Hybrid optimization techniques have gained significant interest in recent years as they can integrate different search mechanisms to achieve better improvement of complex combinatorial problems. To achieve more balanced solution diversification and intensification, hybrid algorithms combine exploration-oriented strategies with exploitation-oriented ones. This stands them in good stead when it comes to solving large scale optimization problems, where traditional meta-heuristic approaches may converge (well) before the solution region has been thoroughly explored.

Due to their ability to combine different search mechanisms and improve optimization performance in complex problems [9], [15], [16]. For example, in smart manufacturing systems, applying these methods to resource allocation in IoT networks and large-scale scheduling tasks was one of the most important trends [14], [17], [18]. Nevertheless, it is true that many hybrid algorithms alter all their populations by means of local search, thus causing unnecessary computational overhead and affecting scalability in some cases.

In response to this issue, this paper proposes a hybrid metaheuristic algorithm which integrates the GA with CS for solving QAP. The proposed GA–CS framework combines the global exploration capability of GA with selective use of CS as an intensification operator for elite individuals. Same time as McColl Lang's pioneering work in 1991, the method of selective hybridization can both refine the solutions and at the same time inherit the diversity of the population, avoiding any additional computational overhead. Statistical significance is tested by the Wilcoxon signed-rank test [19], which enables a stable evaluation in performance consistency.

The algorithm is compared with classical metaheuristic approaches including GA, CS, and hybrid GA–PSO to assess improvements in solution quality and convergence behavior. The study therefore proposes a hybrid GA–CS optimization framework for adoption in the solution of QAP that conveniently overcomes existing approaches limitations. The proposed method seeks to combine the global exploration ability of GA and local exploitation power of CS. The main contributions of this work are summarized below:

- Development of a GA-CS optimization framework for hybrid optimization of the QAP.
- The CS was equipped with an elite-based local refinement mechanism to improve quality and extend its application.
- Quadratic assignment problem library (QAPLIB) engineering test bed to check the results further.
- The Wilcoxon signed-rank test was used to analyze the validity of the obtained values.

2. RESEARCH METHOD

The GA, with its strong global search capability and CS algorithm's excellent ability for local exploitation, combines in this hybridized version to solve the QAP. It exploits torn populations to preserve diversity and peripheries to do local intensification of only the highest quality solutions.

2.1. Problem formulation

This facility layout has been described as the QAP because we want to assign n facilities to n locations so that (as much as possible) interpersonal cost do not appear to be too high. In a formal mathematical statement, the objective is expressed by following formula:

$$min\ Z\ =\ \Sigma_{\{i=1\}}^{\{n\}}\ \Sigma_{\{j=1\}}^{\{n\}}\ f_{ij}\ \cdot\ d_{\{\pi(i)\pi(j)\}}$$

where f_{ij} represents the flow between facilities i and j, $d_{\{\pi(i)\pi(j)\}}$ denotes the distance between assigned locations, and π is a permutation representing the assignment solution.
Subject to: each facility is assigned to exactly one location and each location is assigned to exactly one facility.

2.2. Hybrid genetic algorithm-cuckoo search framework

The process of hybridization, as proposed here, is divided into a pair of stages. As the first step, global search is done with GA. By way of its crossover and mutation operators, large numbers of candidate solutions are obtained. The second phase is a CS algorithm that selectively applies episode-exploitation to fine-tune some of the most promising specimens out there, by using Levy-based flight movements at each step [20]. This way not only is solution quality improved but computation-al cost is not much increased [21]–[25]. Many population-oriented metaheuristic algorithms have been successfully utilized to deal with different complex optimization tasks. Introduced by Shi and Eberhart [21], PSO has shown its ability in global search for many engineering problems. Similarly, tabu search (TS) is a mature metaheuristic using adaptive memory structures for climbing out of local optima and improving solution quality [22]. The CS algorithm [23] is relatively new but has become widely used because of its simplicity and efficiency for dealing with very large search spaces (with the use of Lévy flights). The QAPLIB has been one of the most frequently used benchmark repositories to evaluate optimization algorithms [24]. Also, cat swarm optimization (CSO) is a relatively new swarm-based algorithm which has been successfully applied to many optimization tasks appeared in the literature and shown very competitive results compared with other swarm-based algorithms [25].

CQAP uses a hybrid optimisation framework that combines exploration GA and exploitation ability CS algorithm, which is developed to effectively address the QAP. The proposed algorithm: Algorithm 1 initializes a population of candidate solutions through genetic operators such as selection, crossover and mutation. Once effective solutions are generated, local search is applied to explore the candidate solution and obtain better quality solutions in an adaptive fashion by means of CS mechanism. The individual components of this hybrid design seek to balance global exploration against local exploitation such that faster convergence is achieved and high-quality solutions for large scale QAP instances can be obtained.

2.3. Description of algorithms

Algorithm 1 shows a summary of the main procedural steps of the proposed hybrid algorithm.

Algorithm 1. The hybrid GA–CS for QAP
- First, randomly set up a population of P feasible solutions.
- The fitness of every solution is judged by the QAP objective function.
- According to the generations, be sure to make g=1 from the beginning.
- Unless g≤G do:
- Using tournament selection, a parent solution is chosen.
- Crossing occurs with probability pc that is either true or false.
- Since diversity must be maintained, we may as well apply mutation with probability pm.
- At the same time, the fitness of our offspring must be evaluated3.
- Eligible solutions: select the top E.
- As for elite solutions, we apply CS local refinement.
- If improved solutions again appear, the best solutions get h_i replaced.
- The next generation population is formulated.
- Update the best solution ever found.
- $g = g + 1$.
- Finally achieve that.

To return the best output.

2.4. Computational complexity

The introduced hybrid algorithm has a computational complexity which mainly depends on the population size, number of generations and dimension of problem. Fitness evaluation is the costliest part and requires about $O(n^2)$ operations for each candidate solution. Thus, the approximate upper bound for overall complexity of the algorithm is $O(G \cdot P \cdot n^2)$ and CS is only applied to elite individuals (to constrain computational overhead, while ensuring scalability).

2.5. Parameter settings

The main parameter values of this algorithm are population size, crossover probability, mutation probability, elite size, and number of generations. These parameters result from test experiments that, although seemingly inconclusive in nature, strive to strike a balance between exploration and exploitation.
Objective: minimize $Z = \Sigma \Sigma f_{ij} * d_{\{\pi(i)\pi(j)\}}$

Subject to each facility may be assigned to only one location. The proposed hybrid GA–CS has some control parameters, such as population size (PS), crossover probability (PC), mutation probability (MM) elite size (ES), and number of generations (NG). The parameters were chosen based on initial experimental tests which gave a good tradeoff between exploration and exploitation in the search. Table 1 shows parameter values employed throughout the computational experiments.

Table 1. Parameter settings of the proposed GA–CS algorithm

Parameter	Value (unit)
Population size (P)	50 individuals
Number of generations (G)	200 generations
Crossover probability (p_c)	0.8 (dimensionless)
Mutation probability (p_m)	0.1 (dimensionless)
Elite size (E)	5 individuals

3. RESULTS AND DISCUSSION

Experiments were executed on problem instances from the QAPLIB library, where the n parameter varied from 20 to 100. It's same as the proposed GA–CS algorithm was compared with several optimization algorithms, including the standard GA, PSO, CS, and the hybrid GA–PSO algorithm.

Three baseline methods, namely GA, CS, and the hybrid GA–PSO method. The evaluation metrics involved best objective value, relative percentage deviation (RPD), the mean value for solution quality and standard deviation of solution quality.

Table 2 shows how the evaluated algorithms perform in terms of RPD for selected QAPLIB benchmark instances. In most tested instances, the newly proposed GA–CS algorithm achieved lower RPD values, indicating solutions closer to the best-known results.

Benchmark instances to evaluate the proposed algorithm; we performed comparative experiments with respect to standard GA, CS and hybrid (GA-PSO) algorithms within the same experimental environment. The goal was to evaluate solution quality, convergence behavior and general robustness for varying problem sizes. To verify the performance of this novel algorithm, numerical results have been compared with a variety of popular optimization strategies commonly used in literature including; i) GA [6], ii) PSO [7], and iii) CS problem [23] as well as GA-PSO hybrid method. Such algorithms have been chosen as they cover the main and frequently used metaheuristic, and hybrid optimization methods for combinatorial problems.

Table 2. Comparative RPD results

Instance	Best known	GA	CS	GA-PSO	GA-CS
nug20	2570	6.11	6.32	4.91	3.12
nug25	3744	6.44	6.51	5.02	3.47
nug30	6124	5.91	6.02	4.85	2.94
chr12a	9552	4.82	5.11	3.98	2.65

The results in Table 2 demonstrate that the proposed GA–CS algorithm has a much smaller RPD value on most benchmark instances. A lower RPD value indicates that the best solutions found are closer to those from QAPLIB. These results show that the integration of GA with CS resulting in combining exploration and intensification mechanisms can be a good option to further enhance optimization performance. A Wilcoxon signed-rank test was used to evaluate the statistical significance of the obtained results at a level of 0.05. Statistical analysis shows that the proposed GA–CS algorithm provides significant improvements over just using the original GA or CS algorithms. However, for a small number of cases where there is no statistical significance in differences between GA–CS and GA–PSO it presumably means both hybrids are performing similarly well overall, as shown in Figure 1.

This image compares RPD performance of various algorithms and draws attention to the limits of each. Here low values indicate problems with a given algorithm and high values mean the opposite. Figure 1 is a demonstration of the RPD performance of several algorithms. The lower RPD value a solution has, the more optimal it is known to be. The results clearly show that the proposed GA–CS algorithm has lower RPD values than GA and CS, which shows that our solution accuracy has also improved greatly. As you can see, the GA-PSO has a larger blind area than anything else shown. The improvement is attributable to retreat individual locations as elite individuals when applying CS to enhance local refinement while preserving the overall diversity.

A Wilcoxon signed-rank test was performed at a significance level of 0.05 to determine statistical significance. The results show that the improvements brought by our method are significant against the background of most instances in all benchmarks, when compared with either pure GA or pure CS but not with PSO (there's no statistical difference). This means that the performance improvements are true and not simply a random occurrence [10].

As shown in Figure 1, RPD performance comparison across various algorithms, by using this kind of combination we were able to considerably reduce deviations from ideal solutions. This is mainly because only individual cuckoo's performance in CS is invested in, while overall diversity.

As can be seen from Figure 2, we have discussed this paper in detail. The proposed GA–CS algorithm achieves better convergence (that is to say, for lower function values) than the original GA and CS algorithms. Next, results show that this improvement is due to an appropriate balance between global exploration via GA population-based search plus local exploitation by CS tuning members of the elite solutions.

Figure 1 comparative analysis of GA, PSO, CS and the hybridized algorithms GA–PSO and proposed presented algorithm based on average routing cost. The obtained solution quality and other results of the different solutions applied are compared against each as shown in Table 2, where a minimum relative percentage deviation is achieved with respect to the standard SIMAP model when using hybrid framework.

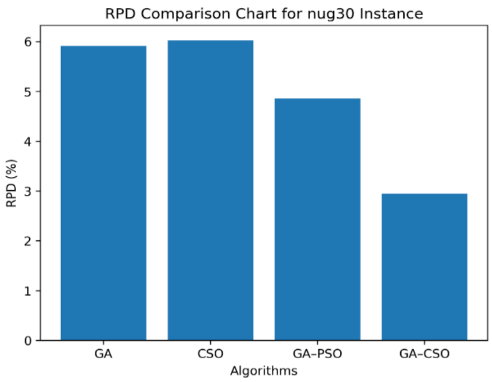

Figure 1. RPD comparison among GA, CS, GA–PSO, and GA–CS for the nug30 instance

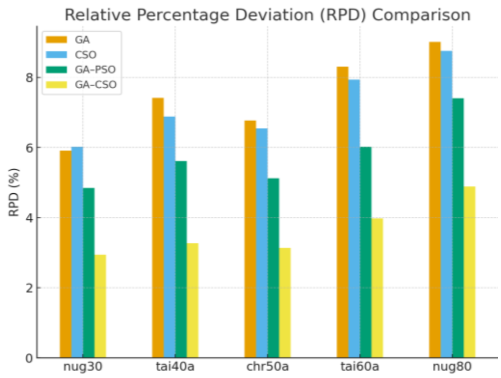

Figure 2. Convergence behavior of the compared algorithms on selected QAPLIB instances

Taking a computational perspective, the proposed hybrid algorithm is just as fast in terms of time but delivers far better solutions. Local optimization costs more cycles, but the extra computation is limited thanks to the fact that CS works only on those elite individuals. This selectiveness in intensification reduces computational load enormously compared with searching locally across the whole swarm.

Compared to the GA-PSO hybrid, GA-CS hybrid gets comparable or better results for a smaller number of variable settings [9]. That will make easier the actual implementation and settings of these parameters. Rules for you to follow along with explain exactly what "elitism" is, with the effect that local search may sometimes be used wherever it helps broaden exploration and helps one avert landing into a bad valley or at non-optimal value. The hybrid algorithm was particularly useful in the middle-sized optimization problems, where an intermediate balance between global and local steps can be critical. The developed algorithm showed stability and adaptability. Although the approach has good overall performance, it is relatively picky for non-deterministic parameters such as the number of subpopulations and electromagnetic width in each generation. Option B could well look at the question of automatic selection and parallelism for adjusting parameters. Free content committing methods that allow you to pay out or not based on analysis only the method adopted is analyzed over almost any job type of worker to obtain systematic free tricks for making up requirements gives far reaching implications.

4. CONCLUSION

In this research, the authors presented an innovative GA-based structured correction technique integrated with the CS algorithm to address QAP. This innovative method uses both GA's capacity to search globally and CS's ability to search locally to improve the quality and variety of elite solutions. Our hybrid technique works better than the classic GA, CS, and GA–PSO algorithms when tested with the well-known QAPLIB data. The Wilcoxon signed-rank test findings also reveal that all displays with high dependability and strong variation are delivered. Local search is used sparingly when it comes to optimization features. It keeps the algorithm from using too much processing power and lets it find a compromise between exploring and taking advantage of it. The proposed optimization framework can solve hard combinatorial optimization problems; hence it might also be used for those challenges. In future endeavors, we will concentrate on adaptive parameters to be used control techniques and parallelism for substantial issues, alongside investigating the application of the hybrid framework in multi-objective optimization.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The contributors assert they do not possess no recognized competing commercial interests or interpersonal affiliations that might be perceived as influencing the findings presented in this study.

DATA AVAILABILITY

All the information used to conduct this study are freely accessible to the public through the QAPLIB. Within the paper, you will find all the necessary facts that back up the results of this investigation.

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