Improving the Solution Quality of Quadratic Assignment Problems using Harmony Improvised Consultant Guided Search Technique

Mrs T Amudha, Dr B L Shivakumar

Abstract - Nature- Inspired metaheuristics is a kind of heuristics that imitate the problem solving behavior from nature. This field is much closely related to the domain of Artificial Intelligence. Optimized utilization of resources is the need of the hour in any manufacturing system. A properly planned schedule and assignment is often required to facilitate optimization. In this paper, one of the significant types of optimization problems, the quadratic assignment problem was considered for study. Benchmark problem instances from OR library were chosen and solved by implementing Consultant guided search heuristic and a proposed heuristic, Harmony improvised Consultant guided search. Computational comparison of these techniques on various benchmark instances had clearly shown the effectiveness of the proposed hybrid technique in solving complex combinatorial optimization problems and the improvement in optimal solutions.

Keywords – Combinatorial optimization, Consultant Guided Search, Harmony Search, Metaheuristics, Nature-inspired computing, Quadratic Assignment Problems.

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1 INTRODUCTION

Assignment problems are considered as an elementary structure in combinatorial optimization due to its programming composition. These problems can often be figured out as sub-problem in many complex problem classes. Besides theoretical magnitude, assignment problems find inherent applicability in research areas ranging from facility allocation to robotic task allocation [14]. Assignment Problems belong to NP-hard combinatorial optimization problem category and have always remained as one of the great challenges in combinatorial optimization. Nature Inspired Computing is an upcoming area of research that aims at developing innovative computing techniques by observing how nature behaves in various situations to solve complex problems [3]. Based on the observation from nature a problem solving strategy can be formulated. The strategy can be used to design an initial model and remodeling it until a near perfect working model is obtained. The resulting model may also find certain new and unknown mechanisms. Principles such as survival of the fittest and law of jungle are used to develop the nature-inspired approaches [6]. NIC techniques are highly adaptable that they can be applied to wide range of problems and can be dealt with unseen data and even incomplete data. They have decentralized control of computational activities. Metaheuristic are algorithmic templates used to specify problem-independent optimization strategies, which can be instantiated in order to define problem-specific heuristics [2].

In computer science, metaheuristics designates a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Metaheuristics make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics do not guarantee an optimal solution in most cases. Many metaheuristics implement some form of stochastic optimization. Metaheuristics have been most generally applied to problems classified as NP-Hard or NP-Complete by the theory of computational complexity. Some of the most successful metaheuristic conceived in the last few years are Tabu Search, Simulated Annealing, Genetic Algorithms and Memetic Algorithms, Ant Colony Optimization, Bacterial Foraging Optimization, Bee algorithms and Harmony Search. They are population-based methods that make use of the global behavior that emerges from the local interaction of individuals with one another and with their environment.

Consultant Guided Search (CGS) is a relatively new metaheuristic algorithm for solving combinatorial optimization problems [5]. CGS is a population-based method that takes inspiration from the way people make decisions based on suggestion received from consultants. Though human behavior is complex, CGS uses only simple rules for decision making to be followed by virtual people. Besides, there is no centralized control structure in CGS, and the group behavior is performed on a self-organization

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basis. These characteristic features include CGS in the metaheuristic family. In CGS, virtual persons are represented as agents, which collaboratively solve complex combinatorial optimization problems. An individual of the CGS population is an agent, which can simultaneously act both as a client and as a consultant. As a client, the agent constructs a solution to the problem. As a consultant, the agent provides advice to clients. At each step of the solution construction, there are several variants a client can choose from. The variant recommended by the consultant has a higher probability to be chosen, but the client has the freedom to opt for any of the other variants, based on some heuristic selection. The client agent chooses a consultant agent based on its personal preference and on the agent's reputation. The reputation of a consultant agent increases with the number of successes achieved by its client agents. The exact details of how reputation and personal preference are used in order to opt for a consultant are specific to each class of application of CGS.

In general, the reputation of consultants fades over time. A consultant needs its clients to constantly achieve success, in order to upgrade its reputation. If the consultant agent's reputation sinks below a minimum threshold, a sabbatical leave will be offered, during which the agent should stop advice to clients and instead start searching for a new solution construction strategy for future consultation. If the agent in sabbatical mode has identified a better strategy, it accommodates itself to the new strategy and act accordingly, once it comes out of sabbatical to normal mode. However, the method used to adjust the strategy is specific to each of the metaheuristic instantiation. The consultant agents are ranked based on the best result obtained by the clients working under its guidance. CGS metaheuristic implementation requires definite representations for reputation fading over time, minimum threshold of reputation and ranking of consultant agents. On close observation, it could be recognized that CGS has certain conceptual similarity with few other popular metaheuristics. The reputation fading phenomenon in CGS is found much similar to the pheromone evaporation in Ant Colony Optimization. The construction of a new strategy during the sabbatical leave resembles the escape mechanism used in Reactive Tabu Search. Maintaining a list of high quality solutions in CGS can also be related with effective candidate list maintenance found in some ACO variants like population-based ACO.

Harmony Search is a popular nature-inspired, phenomenon mimicking meta-heuristic algorithm inspired by the musical process of searching for a perfect state of harmony [16] [17]. HS algorithm was developed in an analogy with music improvisation process where music players improvise the pitches of their instruments to obtain better harmony. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques. In the HS algorithm, musical performances seek a perfect state of harmony determined by aesthetic estimation, as the optimization algorithms seek a best state (i.e., global optimum) determined by objective function value. It has been successfully applied to various optimization problems in computation and engineering fields including economic dispatch of electrical energy, multicast routing, clustering, optimum design, traveling salesman problem, parameter optimization of river flood model, design of pipeline network, and design of truss structures [15]. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques [7], which are represented in Table 1.

Table 1: Optimization Terms in Musical perspective (Source: Azmi et al., 2010)

Musical terms	Optimization terms
Improvisation	Generation or construction
Harmony	Solution vector
Musician	Decision variable
Pitch	Value
Pitch range	Value range
Audio-aesthetic standard	Objective function
Practice	Iteration
Pleasing harmony	(Near-) optimal solution

The HS algorithm does not require initial values for the decision variables. Furthermore, instead of a gradient search, the HS algorithm uses a stochastic random search that is based on the harmony memory considering rate and the pitch adjusting rate so that derivative information is unnecessary. Compared to earlier meta-heuristic optimization algorithms, the HS algorithm imposes fewer mathematical requirements and can be easily adopted for various types of engineering optimization problems such as traveling salesman problem, tour routing, music composition, Sudoku puzzle solving, water network design, dam operation, vehicle routing, structural design, and other industrial problems [15], [18].

The Quadratic Assignment Problem (QAP) was introduced by Koopmans and Beckmann back in 1957 to model a plant location problem [12]. The number of real life problems that are mathematically modeled by a quadratic assignment problem has been continuously increasing even today. It is one of fundamental NP-hard combinatorial optimization problems in the branch of Operations Research in mathematics, from the category of the facilities-locations problems. From a computational point of view,

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quadratic assignment problems are very difficult problems. It is proven that QAP is NP-hard and even with today's fast multi-core CPUs, it is still considered hard to solve problems of a modest size as n = 30 within reasonable time limits [11]. One of the major applications of the QAP is in location theory. QAP can be described as the problem of assigning a set of "n" facilities to a set of "n" locations with $n!$ possible assignments The objective is to find the assignment that minimizes this cost.

The main goal of Quadratic Assignment Problem is to find an assignment (i.e., a permutation p ∈N) of all facilities to all locations, such that the total cost of the assignment is minimized.

The Objective of the Quadratic Assignment Problem is as given below:

$$\min_{p \in N} f(P) = \sum_{i=1}^{n} \sum_{j=1}^{n} f_{ij} \cdot d_{p(i)p(j)} \longrightarrow \quad (1)$$

Where, $F = (f_{ij})$ be the flow matrix, whose $(i, j)^{th}$ element represents the flow between facilities i and j.

$D = (d_{ij})$ be distance matrix, whose $(i, j)^{th}$ element represents the distance between locations i and j.

P = the total number of permutations or arrangements for assigning facilities to locations ($n!$ possible assignments).

The major concern when dealing with larger instances of QAP is that the number of permutations grows extremely fast in the same way as with the traveling salesman problem. This indicates that QAP problems are very much time consuming to generate and calculate every single permutation. This is one of the main reasons why different algorithms have been developed for QAP [11], [13].

In this paper, we present an improved hybrid technique, HICGS (Harmony Improvised CGS) to solve QAP instances. In CGS solutions, Harmony search was used for improvising the search strategy of the consultant which was found to improve the assignment of facilities to locations in QAP. Both CGS heuristic and our proposed strategy HICGS were implemented and applied to various benchmark instances of QAP, taken from the QAP-Library [10]. These instances are worth solving as they are considered as the most significant, classical and complex CO problems known to be NP-hard. Experimental results have clearly shown the effectiveness of our proposed technique HICGS in solving large and complex instances of QAP and the improvement in optimal solutions when CGS was hybridized with HS.

2 RELATED WORK

Zong Woo Geem et al., (2005) applied Harmony search to a TSP-like NP-hard Generalized Orienteering Problem which is to find the utmost route under the total distance limit while satisfying multiple goals. The results of HS showed that the algorithm could find good solutions when compared to those of artificial neural network [16].

Sukayapong Ngonkham and Panhathai Buasri (2009) presented harmony search algorithm to solve economic dispatch (ED) problem in the power system integrating wind energy conversion system (WECS). Three optimization techniques, genetic algorithm (GA), interior point methods (ITP) and HS were applied to solve ED when system connecting and disconnecting to WECS. The results showed that HS can give the better solution than the others. In the comparison with GA, HS and ITP, HS had better than GA 3.2% and better than ITP 1.6%. Moreover total cost reduction when the system connected to WECS computed by HS was reduced to 8% per day [8].

Quan-Ke Pan et al., (2011) proposed a local-best harmony search algorithm with dynamic sub-harmony memories, namely DLHS algorithm to minimize the total weighted earliness and tardiness penalties for a lot-streaming flow shop scheduling problem with equal-size sub-lots. Computational experiments and comparisons showed that the proposed DLHS algorithm generated better or competitive results than the existing hybrid genetic algorithm and hybrid discrete particle swarm optimization for the lot-streaming flow shop scheduling problem with total weighted earliness and tardiness criterion [9].

Mohammed Azmi Al-Betar and Ahamad Tajudin Khader (2010) applied a HS and a modified harmony search algorithm to university course timetabling against standard benchmarks. The results showed that the proposed methods were capable of providing viable solutions in comparison to previous works. The results of modified harmony search algorithm (MHSA) basically outperformed those obtained by basic harmony search algorithm significantly. However, the computational time needed for MHSA is longer [7].

Dexuan Zou et al., (2010) have used a novel global harmony search algorithm (NGHS) to solve task assignment problem, and the NGHS algorithm had demonstrated higher efficiency than the improved harmony search algorithm on finding the near optimal task assignment. The results illustrated that the NGHS algorithm had strong capacity of space exploration throughout the whole iteration due to the utilization of genetic mutation [18].

Serban Iordache[SI10] has introduced Consultant-Guided Search, a new metaheuristic for combinatorial optimization problems, based on the direct exchange of information between individuals in a population. It was discussed in this paper, how Consultant-Guided Search can be related to other metaheuristics for combinatorial optimization and also argued that CGS is a hybrid metaheuristic since a series of concepts were borrowed from other optimization techniques to design CGS. The author has exemplified the application of this metaheuristic to a specific class of problems by introducing the CGS-TSP algorithm, an instantiation of Consultant-Guided Search for the Traveling Salesman Problem (TSP). Its experimental results have proven that the solution quality obtained by CGS-TSP is comparable with or better than that obtained by Ant Colony System and MAX-MIN Ant System [5].

Farhad Djannaty and Hossien Almasi [DH07] have applied a Multi Hybrid Genetic Algorithm for solving Quadratic Assignment Problem. The key feature of Multi Hybrid Genetic Algorithm is the hybridization of three metaheuristic tabu search, simulated annealing and ant system with genetic algorithm. They tested their approach with number of standard test problems and it was proven that, their approach is also one of the best methods for solving Quadratic Assignment Problems [4].

Victor V Migkikh, Alexander P Topchy et al [MTT00] have described a novel hybrid algorithm that combines the advantages of local and global search techniques for the solution of the Quadratic Assignment Problem. They used genetic algorithm to provide global search, while local optimization was implemented as a local improvement procedure in a modified version of a partially-mapped crossover. These features along with modifications in the mutation mechanism have shown a good level of efficiency in conditions of high epistasis peculiar to the QAP [13].

Alfonsas Misevicius [AM06] have applied an extension of the hybrid genetic algorithm for the well-known combinatorial optimization problem, the quadratic assignment problem. This extension was based on the "fast hybrid genetic algorithm" concept. An enhanced tabu search was used in the role of the fast local improvement of solutions, whereas a robust mutation strategy was made responsible to maintain a high degree of the diversity within the population. Obtained results have confirmed that the hybrid algorithms are the most suitable heuristic approaches for Quadratic Assignment Problems. They suggested that the Hybrid genetic algorithm could be modified to suit other types of combinatorial optimization problems [1].

Shigeyoshi Tsutsui [ST08] has proposed several types of parallel Ant Colony Optimization algorithms with symmetric multi-processing for solving the quadratic assignment problem. These models include the master-slave models and the island models. They evaluated each parallel algorithm with a condition that the run time for each parallel algorithm and the base sequential algorithm are the same. Their results suggested that using the master-slave model with increased iteration, ACO algorithms gave promising solutions for QAP [11].

3 HYBRID HICGS METAHEURISTIC FOR QAP

In our hybrid Harmony Improvised Consultant Guided Search (HICGS) technique, the solution construct strategy of CGS was enabled by using the technique of harmony improvisation over a period of time for a fixed number of iterations, till a feasible solution is obtained. A musically pleasing harmony can be found based on three musical rules [15] : (i) by playing a note from harmony memory (HM); (ii) by playing a note which is closer to another note stored in HM; and (iii) by playing an arbitrary note from the entire note range. Combination of these rules allows finding a musically pleasing harmony which is equivalent to the best state. Adaptation of these rules to the optimization problems is as follows: (i) generate a new solution vector from HM (memory consideration); (ii) replace a decision variable with a new one which is much closer to the current one (pitch adjusting); and (iii) generate a solution vector from the possible random range (random selection). Combined utilization of these rules allows identification of the optimal or near optimal solutions for optimization problems.

The working principle of HS algorithm is very different from classical optimization techniques. HS algorithm uses a random search, which is based on the harmony memory considering rate and the pitch adjusting rate. Compared to earlier meta-heuristic optimization algorithms, the HS algorithm imposes fewer mathematical requirements and can be easily adopted for various types of engineering optimization problems. Due to the natural phenomenon of music improvisation, the reputation of more number of consultants was not allowed to sink below a minimum threshold. And hence, very few poor performing consultants will take a sabbatical leave, during which period; they will stop offering advice to clients and will instead start searching for a new strategy to use in the future [5].

Also, when the consultants complete their sabbatical, and if their current solution constructs strategy was not improved than the best-so-far strategy, then a pitch adjustment was performed to offer possible chances to the consultant to improve their performance and to offer consultation to clients. The optional local search technique, present in original CGS algorithm was not required in our hybrid HICGS approach; since local optima can also be well handled by HS as the solution improvement strategy, whereas global optima can be handled by CGS metaheuristic. In HICGS, the best features of harmony search algorithm were incorporated into CGS to obtain improved consultant strategy setting to obtain better optimal solutions. Pseudo code of the proposed hybrid HICGS metaheuristic is given below.

In our proposed HICGS, the harmony search technique searches for the possible assignment of all facilities to all location based on the following steps namely:

- *Initialize the problem and HS parameters*
- *Initialize the harmony memory*
- *Improvise a new harmony*
- *Update the harmony memory*

Pseudo code of the proposed hybrid HICGS

```
procedure HICGSMetaheuristic ( )
  create a set 𝒫 of virtual persons
  for each p ∈𝒫 do
      setSabbaticalMode (p)
  end for each
  while (termination condition not met) do
    for each p ∈𝒫 do
        if actionMode[p] = sabbatical then
  currStrategy[p] ← HarmonyImprovisationStrategy (p)
        else
            currCons[p] ← chooseConsultant (p)
            if currCons[p] ≠ null then
currSol[p] ← constructSolution (p, currCons[p])
            end if
        end if
    end for each
for each p ∈𝒫do
if actionMode[p] = sabbatical then
 if currStrategy[p] better than bestStrategy[p] then
        bestStrategy[p] ← currStrategy[p]
  end if
else
   c ← currCons[p]
 if c ≠ null and currSol[p] is better than all solutions
  found by a client of c since last sabbatical then
  successCount[c] ← successCount[c] + 1
strategy[c] ← PitchAdjustmentStrategy (c, currSol [p])
 end if
 end if
end for each
  updateReputations ( )
  updateActionModes ( )
end while
end procedure
```

After initializing the problem parameters, the Harmony Memory (HM) matrix is filled with as many randomly generated solution vectors as the size of the HM (HMS). A new harmony vector, $x' = (x_1', x_2' \ldots x_N')$ can be generated by following HM Considering Rate (HMCR), Pitch Adjustment Rate (PAR) or totally random generation as given in equation 2.

$$\begin{bmatrix} x_1^1 & x_2^1 & \ldots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \ldots & x_{N-1}^2 & x_N^2 \\ \vdots & \ldots & \ldots & \ldots & \ldots \\ x_1^{HMS-1} & x_2^{HMS-1} & \ldots & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \ldots & x_{N-1}^{HMS} & x_N^{HMS} \end{bmatrix} \begin{matrix} \Rightarrow & f(x^1) \\ \Rightarrow & f(x^2) \\ \Rightarrow & \vdots \\ \Rightarrow & f(x^{HMS-1}) \\ \Rightarrow & f(x^{HMS}) \end{matrix} \longrightarrow (2)$$

The value of the decision variables for the new vector can be chosen from values stored in HM ($x_1^1 \sim x^{HMS}{}_1$). This method also permits to choose totally random values. HMCR parameter, which varies between 0 and 1, sets the rate whether a value stored in HM or a random value can be chosen, as given in equation 3.

$$\boldsymbol{x_i'} \leftarrow \begin{cases} \boldsymbol{x_i'} \in \{\boldsymbol{x_i^1}, \boldsymbol{x_i^2}, \ldots \boldsymbol{x_i^{HMS}}\} & \boldsymbol{w.p.\ HMCR} \\ \boldsymbol{x_i'} \in \boldsymbol{X_i} & \boldsymbol{w.p.\ (1 - HMCR)} \end{cases} \longrightarrow (3)$$

The HMCR is the rate of choosing one value from historical values stored in HM while (1-HMCR) is the rate of randomly choosing one value from the possible value range. On choosing a new Harmony vector $x' = (x_1', x_2' \ldots x_N')$, pitch-adjusting decision is examined for each component of the new vector as given in equation 4.

$$\boldsymbol{x_i'} \leftarrow \begin{cases} \textbf{Adjusting Pitch} & \boldsymbol{w.p.\ PAR} \\ \textbf{Doing Nothing} & \boldsymbol{w.p.\ (1 - PAR)} \end{cases} \longrightarrow (4)$$

In the pitch adjusting process, a value moves to its neighboring value with probability of PAR, or just stays in its original value with probability (1-PAR). The HMCR and PAR parameters in Harmony Search help the algorithm find globally and locally improved solutions, respectively. If the New Harmony x^{New} is better, in terms of objective function value, than the worst harmony in HM, the new harmony is included in HM and the worst harmony is excluded from HM as stated in equation 5.

$$\boldsymbol{x^{New} \in HM \ \& \ x^{Worst} \notin HM} \longrightarrow (5)$$

4 EXPERIMENTAL RESULTS AND DISCUSSION

This section analyzes the results of the implementation of our proposed hybrid metaheuristics, HICGS in solving benchmark instances of Quadratic Assignment Problems. The test problems for QAP are taken from the QAP Library (QAPLIB) [10]. QAPLIB is a collection of test data sets for quadratic assignment problems proposed by various authors. QAP has remained one of the great challenges in combinatorial optimization as it is still considered a computationally nontrivial task to solve modest size problems, say of size 30.

The following Table 4.11 depicts the parameter settings for harmony search in our proposed HICGS. The constant values considered for our experiment were given in Table 2.

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Table 2: Parameter Settings for proposed HICGS

Parameter	Values	Description
P	Depends on problem size	Number of Virtual persons
β	0.002	Influence of the advertised cost
maxReputation	40	Maximum reputation value
initialReputation	15	Reputation after sabbatical
bonus	6	Best-so-far reputation bonus
r	0.1	Reputation fading rate
sabbaticalduration	5	Sabbatical leave count
Crossover ratio	0.6	Probability of crossover
Mutation ratio	0.03	Probability of mutation
T size	5	Tournament size
NVAR	Depends on problem size	Variables in harmony vector
LOW	0	Harmony minimum range
HIGH	4	Harmony maximum range
BW / FW	0.2	Bandwidth / Fret width
Iterations	1000	Number of improvisations

The benchmark instances of Quadratic Assignment Problem are classified based on authors' names with instances size. The instances size ranges from 12 to 256 and instances of size above 20 are considered to be highly challenging with high level of complexity. In this research work 37 QAP instances of sizes ranging from 20 to 50 were taken into consideration. The optimal solution cost obtained by HICGS in solving QAP benchmark instances were compared with CGS solution and the Best-known solution [10], as listed in Table 3.

Table 3: Optimal Cost Comparison of Benchmark QAP instances

Instance Name	Optimal Cost				Best-Known Solution
	CGS	Gap (%)	HICGS	Gap (%)	
Chr20a	2192	**0**	2192	**0**	2192
Chr20b	2298	**0**	2298	**0**	2298
Chr20c	14142	**0**	14142	**0**	14142
Had20	6929	0.10	6922	**0**	6922
Lipa20a	3698	0.41	3683	**0**	3683
Lipa20b	27146	0.26	27076	**0**	27076
Nug20	2570	**0**	2570	**0**	2570
Rou20	725968	0.06	725538	**0**	725522
Scr20	110376	0.31	110036	**0**	110030
Tai20a	703870	0.06	703498	**0**	703482
Tai20b	122456832	**0**	122455389	**0**	122455319
Nug25	3744	**0**	3744	**0**	3744
Tai25a	1167367	0.01	1167256	**0**	1167256
Tai25b	344365664	**0**	344356746	**0**	344355646
Chr25	3796	**0**	3796	**0**	3796
Kra30a	88900	**0**	88900	**0**	88900
Kra30b	91422	**0**	91420	**0**	91420
Nug30	6124	**0**	6124	**0**	6124
Lipa30a	13188	0.08	13178	**0**	13178
Lipa30b	152849	0.93	151864	**0.29**	151426
Tho30	153943	2.60	150336	**0.27**	149936
Tai30a	1734797	1.61	1713850	**0.41**	1706855
Tai30b	637351302	0.04	637235533	**0.02**	637117113
Tai35a	2382198	6.95	2242272	**1.14**	2216627
Tai35b	243076548	0.37	242247240	**0.03**	242172800
Tho40	255816	12.28	228532	**1.80**	224414
Lipa40a	33538	5.96	31538	**0**	31538
Lipa40b	479324	0.57	476651	**0.01**	476581
Tai40a	2876301	1.15	2856453	**0.46**	2843274
Tai40b	566212712	0.32	564942855	**0.09**	564428353
Sko42	15236	1.98	14956	**0.15**	14934
Sko49	22436	1.93	22004	**0**	22004
Wil50	48540	2.97	47120	**0.05**	47098
Lipa50a	64569	3.83	62093	**0**	62093
Lipa50b	1213409	0.26	1212474	**0.18**	1210244
Tai50a	4468324	1.73	4426190	**0.80**	4390920
Tai50b	398945760	0.85	395654247	**0.03**	395543467

The relative gap analysis for the benchmark instances are depicted in figures Figure 1, Figure 2, Figure 3, Figure 4, Figure 5, Figure 6 and Figure 7.

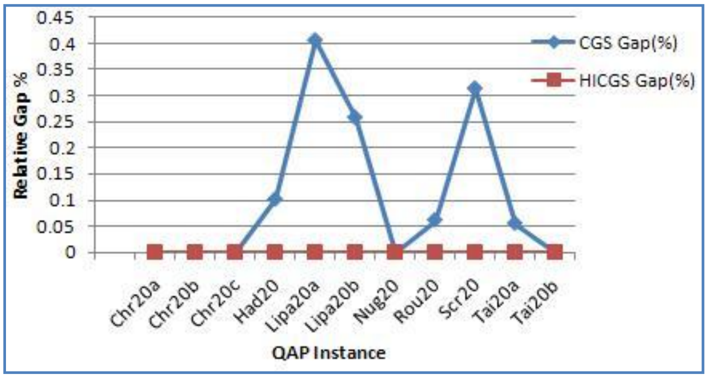

Fig 1: Relative gap comparison of Size-20 QAP instances

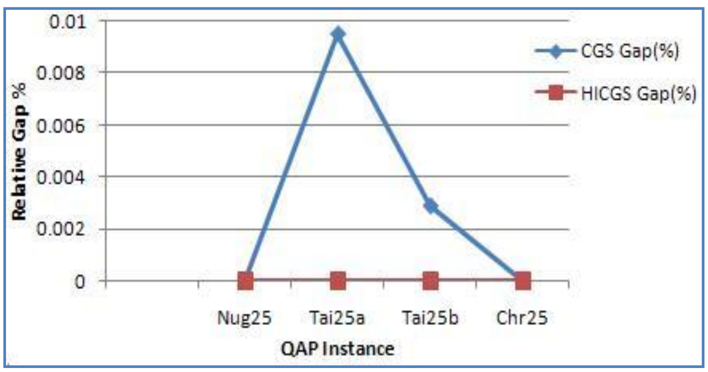

Fig 2: Relative gap comparison of Size-25 QAP instances

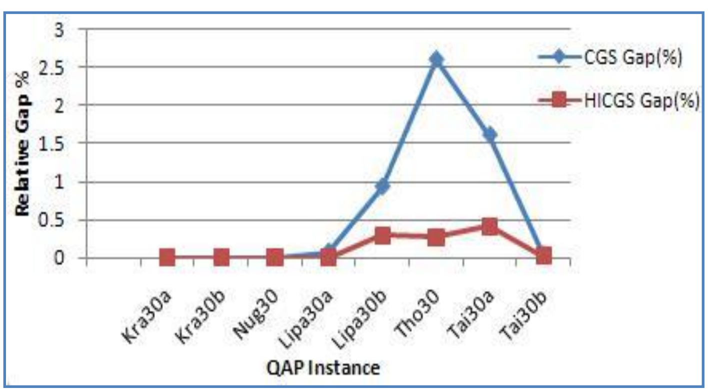

Fig 3: Relative gap comparison of Size-30 QAP instances

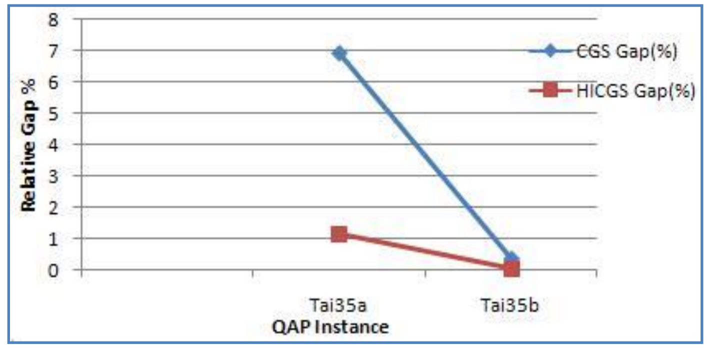

Fig 4: Relative gap comparison of Size-35 QAP instances

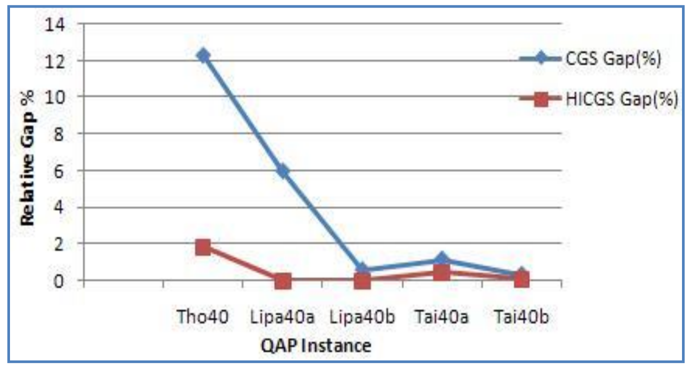

Fig 5: Relative gap comparison of Size-40 QAP instances

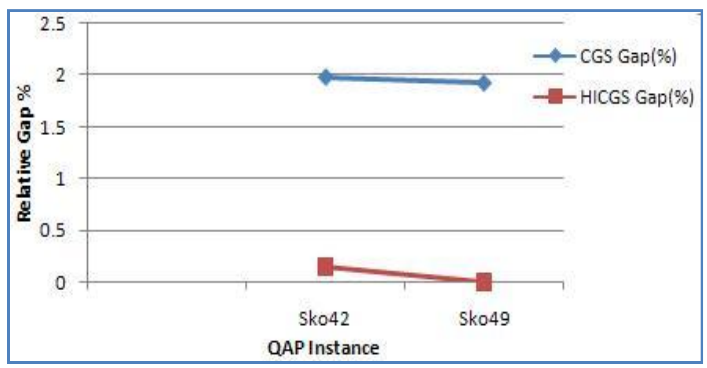

Fig 6: Relative gap comparison of Size-42 & Size-49 QAP instances

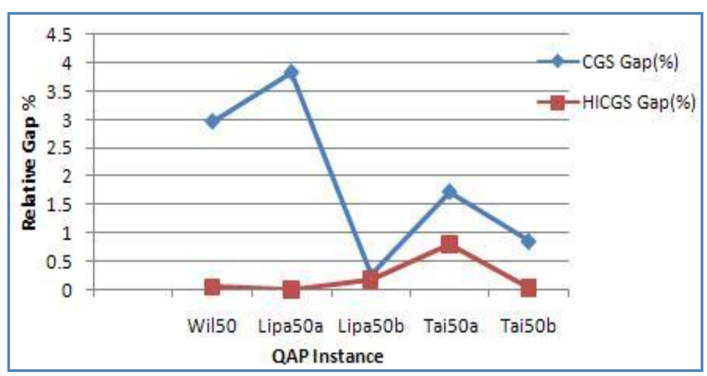

Fig 7: Relative gap comparison of Size-50 QAP instances

It was clearly understandable from the comparison tables and figures that our proposed hybrid method, HICGS is highly competent and achieved improved solutions than CGS metaheuristic. It could be observed from the relative gap values that in most of the cases, the proposed method HICGS have obtained nil gap (gap = 0). For QAP instances of size 20 and size 25, HICGS has arrived at the best known lower bound values and hence the relative gap was zero for HICGS in these cases. For instances of size 30, size 35, size 40, size 42, size 49 and size 50, HICGS has achieved exceptional results and outperformed CGS. Out of 37 QAP problem instances considered, CGS has got exact optima in 11 cases whereas HICGS has got exact optima in 22 cases. HICGS has obtained optimal values much closer to the best known solution and has proven its competency.

4.7 CONCLUSION

In this chapter, we propose a hybrid heuristic HICGS by improvising CGS using harmony search technique. The proposed heuristic technique and CGS were applied to one of the important classes of combinatorial optimization problems, the Quadratic Assignment Problem. The benchmark instances of QAP were taken from the OR-Library and solved by using our proposed, hybrid nature-inspired metaheuristics. The relative gap analysis between the best-known solution and the optimal solution obtained by our proposed method has clearly shown 15% to 60% improvement in HICGS solutions over CGS. This has obviously indicated the competence and efficiency of our methods in achieving improved solutions. Since Harmony Search considers the relationship among neighboring variables exclusively by using ensemble method; it has shown a good performance in the process of hybridization. HICGS has arrived at highly optimal results than CGS in most of the test cases taken for study in this research work. Also, it was identified that CGS algorithm has high scope for modification for solving many other type of combinatorial optimization problems in both static and dynamic categories.

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