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Group Mosquito Host Seeking Algorithm Based Self Organizing Technique for Genetic Algorithm

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Abstract: Genetic algorithms (GAs) are the most important evolutionary computation technique that is used to solve various complex problems that involve a large search space. To have a performance improvement over GA, the concept of Hybrid genetic algorithms that were inspired from the biological behaviour of different living beings was put to use to solve the Non-deterministic Polynomial (NP) complete problems. Hybrid GA can be derived by amalgamating with efficient nature inspired heuristic algorithms like Particle Swarm optimization (PSO), Ant Colony Optimization (ACO), firefly algorithm, cuckoo search, etc.. The grey wolf optimization algorithm has been the recently proposed bio-inspired optimization algorithm that proved as the most recent and best in solving complex problems. In this perspective, Group Mosquito Host Seeking Algorithm based Self-organizing (GMHSA) technique for genetic algorithm has been proposed. The proposed GMHSA model is embedded at the stage prior to genetic operations in order to achieve better exploration and exploitation. The well-known combinatorial optimization problem, Travelling Salesman Problem (TSP), is used as the testbed and the test instances retrieved from the standard TSP library. Various recent and best working hybrid GA models are used to justify the significances of the proposed model. The experimental results show that the proposed algorithm yields better outcome with respect to computational time and also achieve improvement in average convergence rate, irrespective of the size of the test instance, compared to other existing models.

Keywords: Genetic Algorithms, Grey Wolf Optimization, Self-Organizing Genetic Algorithms, Travelling Salesman Problem, Group Mosquito Host Seeking Algorithm.

1 Introduction

In computational science, optimization refers to the selection of a better element from some set of available alternatives. In Genetic Algorithms (GAs), the meta-heuristic and bio-inspired optimization model [1–3], is used to solve large complex problems which deal with large search space proficiently in most cases [4–7]. The GA starts with a population of erratically-produced individuals and generated in generations. At each stage of generation, the quality of each individual in the population is calculated; different individuals are identified from the current population and recombined to form a fresh and new population. This new population is used in the subsequent iterations of the execution to generate other new populations. The algorithm gets stopped on various criteria such as when maximum limit of generations is attained, or the required quality of the individual has been reached [8]. The general model for GA is depicted in Fig. 1.

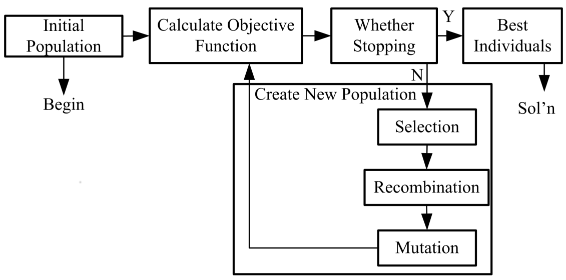

Fig. 1: General model of genetic algorithm

Many researchers endorse hybridization of GA in each phase using problem-specific ideas in order to improve the individual quality and in-turn overall effectiveness of the model [9, 10]. Hybridization of GA

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leaves the algorithm more specific to the problem, at the same-time, the GA performance with respect to the parameters like convergence and computation time can be improved significantly [11, 12]. The traditional GA comprises of a few stages and among those, initialization stage is to be considered as exceptionally essential, where the nature of the final results is identified at the beginning stages [13–15].

Traditionally, the population initialization is performed by random method, which might create a large no. of bad individuals. Then again, actuated models of population seeding procedures lead to the overdue of accomplishments of the fitness capacities with poor convergence qualities. This trade-off inspired the scientists to discover new sets of population initialization procedures for enhancing the stage, particular and general performance of the GAs. Self-organization is one such model, whose purpose is to enhance the performance of the GAs. Self-organization is often characterized as a worldwide request rising up out of neighbourhood associations fittingly [16, 17].

2 Related Works

Self-Organization (SO) is a technique in which individuals coordinate directly with each other in order to improve the quality of the low fitness individuals using the quality information present in the better fitness individuals in the population. It helps to exploit the quality information available in the individual of the current population. In [18], the authors performed a comprehensive survey on various SO techniques proposed in the literature and also the futuristic prospective SO models for GA. Authors guided for different bio-inspired models based on behaviour of Krill Herd, Bull-Eye, and Grey Wolf Algorithm (GWO). Moreover, Self–Organizing Genetic Algorithm (SOGA) with approaches such as social spider optimization, group mosquito algorithm, and Bumblebee colony optimization were introduced before [19].

2.1 Mosquito Behaviour

Though a few species of mosquitoes are harmless or even useful to humanity, most are a nuisance because they consume blood from living vertebrates, including humans [20, 21]. The host-seeking behaviour is concerned with the female mosquitoes. A swarm of mosquitoes arbitrarily search for the host to attack [22–24]. Mosquitoes predominantly use three sensory factors to identify their hosts: they locate bloodhosts by smell, sight and heat. The GMHSA has the following significances [25]:

- an ability to solve large-scale permutation problems.
- its parameters do not depend on algorithm learning.
- it can illustrate composite behaviours.
- it has a complete optimization capability for multi-parameter problems.
- it has robustness, the model is independent of the initial settings, problem-size etc.

Thus, it has been observed that the significant advantages of the GMHSA algorithm over the other existing models and in this perspective, GMHSA-based SOGA can enhance the performance outcome of GA w.r.t. factors like convergence rate and computation time.

3 Proposed Work

3.1 Problem Statement

The research concerned with the proposal of a new hybrid genetic algorithm, in which Group Mosquito Host Seeking Algorithm (GMHSA) is incorporated as a self-organization model to enrich the overall ability to obtain a global optimal solution of genetic algorithm. This research uses both mosquito host-seeking algorithm and self organization algorithm to enhance the effectiveness of the GA. Researchers proposed various self-organization models to improve the GA performance. Applying a nature-based technique as a self organization model in GA is a novel and highly recommended method to increase the GA performance. The developing self-organization algorithm using the group mosquito host seeking algorithm has the effect of the better exploration and possess high possibility to overcome getting struck in local optima.

3.2 Proposed Model

The feeding pattern of populations of mosquitoes is widely called as host selection. The host selection method is identified by determining host-specific tendencies of the vector (i.e., population preferences), on the ecology and behaviour of both the host and the vector, especially with regard to concurrence in space and time, and on the effects of chance and the environment. Mosquito group inclination has conventionally been evaluated by determining the blood meal origin of freshly-fed specimens. This has led to the assessment of the degree of anthropophily via the Human Blood Index (HBI), i.e., the proportion positive for humans in a sample of blood meals [26]. The major steps of mosquitoes host-seeking behaviour as can be summarized as follows:

- The mosquito prefers for carbon dioxide (CO_2) or any kind of smelling component.
- It separates the smell it likes and then moves towards the location with a high concentration of the same smell.

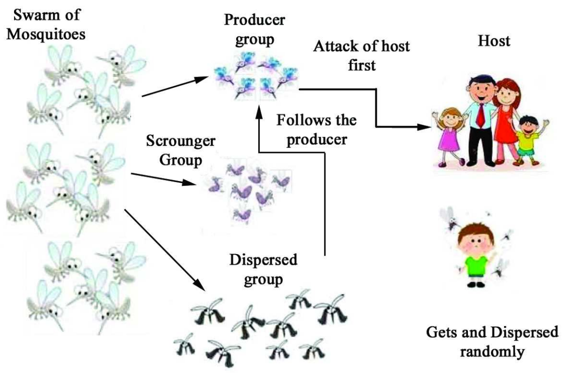

Fig. 2: Group mosquito architecture

The group of mosquitoes seek towards the victim in parallel under the influence of four factors:

1. the behaviour of personal host seeking.
2. the behaviour of aggregate host-seeking.
3. the amount of attraction towards the host.
4. the signal that is associated with social coordination among the mosquitoes group.

A personal utility of a mosquito can be calculated based on the distance between a mosquito and the host which represents the success value of host-seeking for the corresponding mosquito. The more the concentration of Carbon di-oxide(CO_2) and smelling substance, the faster the mosquitoes attempt to seek toward the host. At the time of all mosquitoes stop wandering, being in an equilibrium state, an optimum solution is obtained. The mosquito swarm as in Fig. 2 is classified into three types [27]:

1. The group of producer,
2. The groups of scrounger and
3. The dispersed group.

After classification, groups of each variety perform different activities. The group of producers can continue to preserve its action as it's the best one. When the group of producers identifies the next direction, it will be also considered, based on the previous experience. The group of scroungers move with considering its own knowledge and the knowledge obtained from the producer's experience. The dispersed group randomly generates in the feasible solution space for the problem concerned.

3.3 Group Mosquito-Inspired Self Organization Technique

The flow diagram for the proposed GMHSA-inspired self-organization technique is shown in Fig. 3.

Initially, the first set of population is defined, once it is defined, it is checked if the current generation is greater than the maximum generation. If yes, then the self-organization process using the host-seeking behaviour inspired from mosquito is done. Otherwise, crossover operation is performed followed by mutation and then evaluation. Finally, the obtained solution is checked if it is optimal. If the obtained solution is an optimal solution then it will be taken as the final solution else the cycle repeats from initialization.

Algorithm 1: Algorithm for SO in GA using MHSA

Step 1: Start
Step 2: Select the individual representation
Step 3: Design the fitness function, then population size
Step 4: The generation limit is decided and Initial population is generated and pop is initialized to zero
Step 5: Compare pop and limit
    if *pop is greater than limit* **then**
        go to step 10
    end
    else
        continue
    end
Step 6: Obtain best individual in the population
Step 7: Compare if the best individual is also the fittest individual if yes go to step 10 else start self-organization algorithm
Step 8: After self-organization the selection of the individual takes place
Step 9: The process of crossover and/or mutation is performed which results in new population with pop value incremented by 1
Step 10: Stop

Algorithm 2: Algorithm for self-organization

Step 1: Start with the initialised population (pop_i)
Step 2: Check the fitness value of every individual
Step 3: Segregation is performed based on the fitness value as follows:
  1. If the fitness value is higher than those individuals are considered as producer
  2. Else if the individual has an average fitness value, then they form the scrounger group
  3. Else if the fitness value is bad they form the dispersed group

Step 4: The producer group then passes over a fitness assessment and they move towards the optimal solution
Step 5: The scrounger group obtains the producer knowledge and then moves towards the optimal solution
Step 6: The dispersed group obtains the producer knowledge and then moves towards the optimal solution
Step 7: Finally, the obtained solutions are thus self-organized and they are passed to selection of individuals.

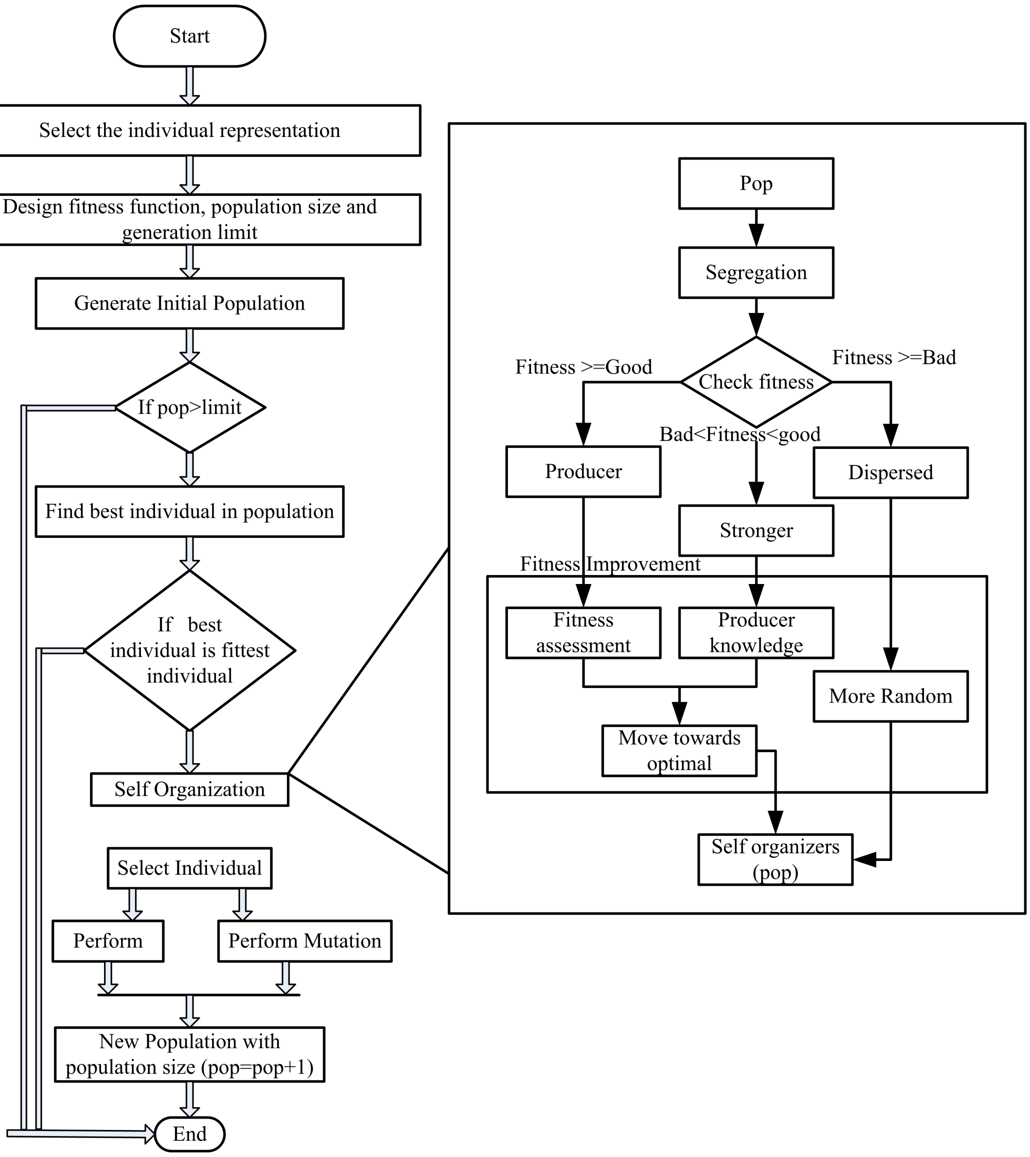

Fig. 3: Flowchart of GMHSA inspired algorithm

3.4 Application Mapping

The application mapping as in Fig. 4 defines the flow of the proposed self-organization genetic algorithm starting from the initialization of the population till the final result of evaluation. Initially, the individual representation of the population is defined. After selecting the initial population which is represented by the symbol “Pop$_i$”, evaluation takes place. The initialized population is checked if it meets the stopping criteria. If the stopping criteria are met then the iteration is stopped and the best solution is selected. If not, GMHSA-SOGA gets executed. In GMHSA-SO, first the initialised population is considered and the fitness value of every individual is evaluated. Based on the fitness value the given population is segregated into three categories, that is, the producer, the scrounger and the dispersed group. The producer group self organizes itself forming an elite group and since it has higher-fitness value and it reaches the host first.

It is then followed by the scrounger group which imitates the movement of the producer group. After copying the movements of producer group, the scrounger group makes its way to the host. Now, the scrounger group is able to reach the host easily as they have the knowledge obtained from the producer group which contains the information about how to reach the host that they need to attack. The mosquitoes that are left over from the group is the dispersed group which moves randomly. The chances of this dispersed group reaching the host cannot be determined, as their probability of ending up into an optimal solution varies on a large scale. Once the self-organization process ends then either the process of cross-over or mutation takes place. In this

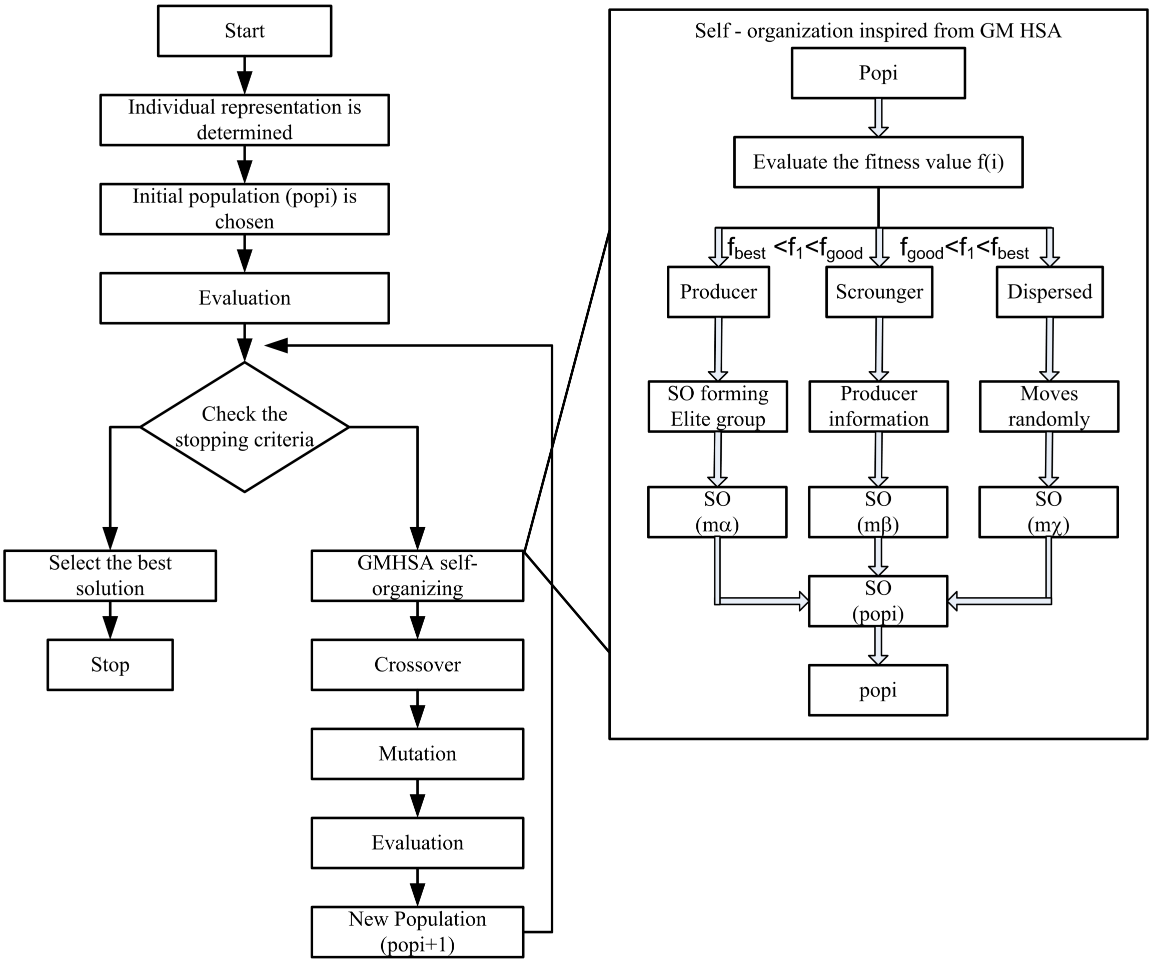

Fig. 4: Flow diagram of SO-inspired from GMHSA

process the properties of the individual are varied and it is then sent for evaluation. After evaluation a new population is then obtained, which is again sent to iterate over the same process. The producer group attacks the host immediately and then the scrounger group gets the information from the producer group and then follows the producer group to attack the host. The next group is the dispersed group which attacks the host using random movement as in the sequence diagram, Fig. 5.

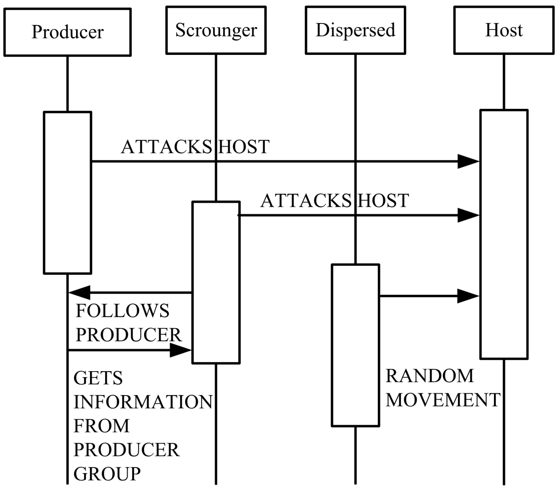

Fig. 5: Sequence diagram for GHMSA

4 Experimentation and Result Analysis

4.1 Testbed Design

In order to implement the proposed model, MATLAB 20011b tool is used and Travelling Salesman Problem (TSP) as the testbed. TSP datasets are retrieved from the TSPLIB library. The vital setting such as size of population is set as 100 and the solution represented is using path representation. The recent and best working techniques like GWO and MHSA are considered to showcase the goodness of the proposed work.

4.2 Performance Factors

The factors used to validate the proposed self-organization technique are determined in order to evaluate the performance of the hybrid genetic algorithm. In this view, the factors used for the validation are computation time and average convergence rate.

4.2.1 Average convergence

Average convergence is the average of the convergence rate of solutions in the result population. It can be represented as,

$$\text{Average of convergence rate} = 1 - \frac{\begin{pmatrix}\text{Convergence value}\\ \text{of population}\end{pmatrix} - \begin{pmatrix}\text{optimal}\\ \text{value}\end{pmatrix}}{\begin{matrix}\text{optimal}\\ \text{value}\end{matrix}} \times 100$$

4.2.2 Computation time

The computation time is the time taken by the MATLAB tool to execute the code and produce the desirable result. It can be referred as the total time required initializing the population and genetic operation on population for the generation limit of times. This can be calculated using the function "*tic and toc*" available in the tool used.

4.3 Result Analysis

In this section, the performance of various genetic algorithm models with hybridization methods such as GWO, MHSA and the proposed GMHSA-SOGA is evaluated. Performance is assessed using TSP instances and discussed using the performance factors as follows.

4.3.1 Computation Time

The total computation time of genetic algorithm influenced by the no. of generations is used in the algorithm. The assessment based on the factor of computation time reveals that, regardless of the size of the test instances, the computation time of the proposed model is consistently better than the existing models used. Though, there is a constant rise in the factor with respect to the increase in the size of the instance. With the same evaluation environment, the performance of other two models; GWO and MHSA, is not consistently same, though the values are nearer to each other. Table 1 represents the experimental results of different self-organization genetic algorithms w.r.t. computation time. The analysis on computation time of different SO genetic algorithm is shown in the Fig. 6.

Table 1: Performance analysis based on computation time (s)

S.No	TSP instances	Optimal value	Existing system GWO	Existing system MHSA	Proposed work GMHSA-SOGA
1	a280	2573	6.57	6.4	5.84
2	att532	27686	38.3	38.22	37.57
3	att48	10628	7.93	7.91	7.9
4	d493	35002	24.94	23.5	23.2
5	d657	48912	26	25.69	24.3
6	eil51	426	7.72	6.29	7.73
7	kroA100	21282	16.49	18.77	14.37
8	pr76	108159	6.99	6.54	6.04
9	rat783	8806	36.01	35.31	33.56
10	tsp225	3916	11.52	10.93	10.48

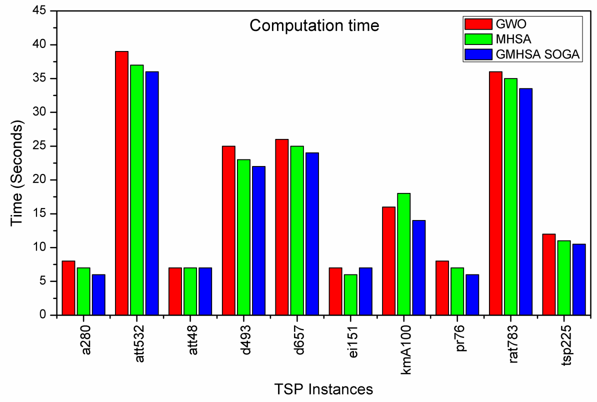

Fig. 6: Computation time based evaluation

Table 2: Performance analysis based on average convergence (%)

S.No	TSP Instances	Optimal value	Existing work GWO	Existing work MHSA	Proposed work GMHSA-SOGA
1	a280	2573	95.42	95.55	96.01
2	att532	27686	93.2	93.29	94.35
3	att48	10628	99.88	99.64	99.89
4	d493	35002	94.5	94.68	95.46
5	d657	48912	92.36	93.5	94.03
6	eil51	426	98.98	99.23	99.58
7	kroA100	21282	96.26	96.3	98.34
8	pr76	108159	97.1	97.5	98.36
9	rat783	8806	92.98	93.28	93.98
10	tsp225	3916	95.63	95.56	95.97

4.3.2 Average Convergence Rate

As mentioned prior, the average convergence of the population is the average quality of the population w.r.t the quality of the optimal solution. This factor reveals how effectively the algorithm moves towards the global optimal solution as a population. The experimental result for average convergence rate of various SOGA considered is shown in the Table 2. From the table, it can be observed that the proposed method offers at least 94% of average convergence for every test instances, at a maximum of

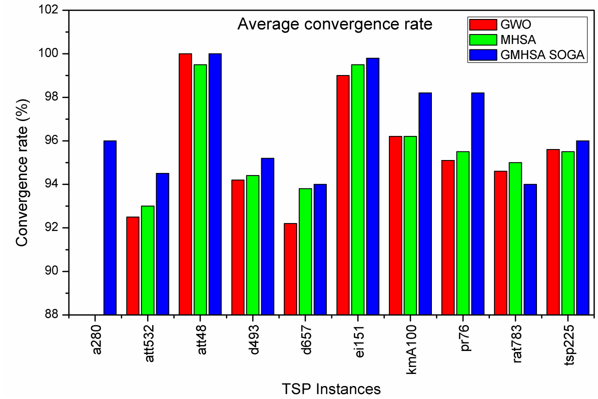

Fig. 7: Average convergence rate based evaluation

99.89 for the instance att48. The average convergences attained by the considered models for the TSP instances are shown in the Fig. 7. From the results, it can be conferred that there is a significant improvement in the average convergence rate of various SOGA models.

4.4 Discussion

The experimentation result analysis shows that the overall performance of the proposed hybrid genetic algorithms with GMHSA-self-organization technique outperforms the existing and best working models. The evaluation is performed on various TSP instances and also for different performance criteria. From the experiment outcome, the average convergence rate and computation time parameters of proposed model shows better improvement than the different existing SOGA. It can also be observed that the proposed GMHSA-SOGA model takes minimum computation time than the other considered methods for every single test instance. Finally, the possibility to obtain the global optimal solution at each generation is higher in the proposed GMHSA-SOGA.

5 Conclusion

In this research, GA performance has been improved using the group mosquito host seeking algorithm as the self-organization in genetic algorithm (GMHSA-SOGA). This hybrid genetic algorithm is used to solve complex and hard problems to achieve efficiency of performance. Thus the GMHSA, is proven to be the most convincing SOGA model to have better computational time and best convergence rate. By integrating self-organization along with the group mosquito host seeking algorithm, the probability of finding better and optimal solution is increased. The result analysis illustrates that the proposed GMHSA-SOGA model is more effective in finding better optimal solutions than the existing methods. For further enhancement, the proposed method can be applied on large sized test instances in order to evaluate the robustness factor. Moreover, amending local search techniques could further improve the proposed SOGA model to obtain the best optimal solution with better convergence rate.

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