Design and Evaluation of a Novel Heuristic Approach for GA and PSO Hybridization

Muhammad Zubair, Jawwad Ahmad, Syed Sajjad Hussain Rizvi, Muhammad Moinuddin

***Abstract*—It is a well-known fact that the performance of classical hard computing is found to be constrained in finding the optimized solution which may not be in the search space. This issue has been resolved by employing various soft computing approaches. A soft computing approach evolves new solutions from within the given search space and then finds the optimal solution based on the given objective(s) and constraint(s). Genetic algorithm (GA) and particle swam optimization (PSO) algorithm are the most employed evolutionary algorithms for solving multi-objective complex problems. Moreover, researchers have proposed three different types of their hybrid combination for extra improved performance. This paper proposes a new hybrid genetic particle swarm optimization (HGPSO) algorithm and evaluates it on a few of the standard testing functions. The evaluation results prove that the proposed hybridization is much better than the three existing hybrid approaches given in the literature.**

***Keywords*Evolutionary algorithms, genetic algorithm, heuristic optimization, particle swam optimization algorithm, hybrid genetic and particle swam algorithm**

I. Introduction

THE computational intelligence is an essential need of multi-objective complex problems. This is because the classical hard computing approaches are found to be constrained to reach to an optimum solution which may not be in the given search space. Technically, the hard computing approaches can only find the local solution but, unable to reach to a global optimum point. On the contrary, the soft computing approaches are designed 'evolve' other possible optimum solutions within the given search space. Moreover, the evolutionary algorithms are reported as the more robust and efficient algorithms to handle complex real-world problems [1, 2]

In the literature, GA and PSO are the most employed evolutionary algorithms [3]. Primarily, both the GA and PSO are the population based optimization algorithms. Research shows that the GA is an extremely robust algorithm that suits to solve multi-objectives problems. However, the efficiency of GA is limited due to its computational complexity [4]. This is because GA requires evolutionary operators like random population generation, cost/fitness evaluation, crossover, and mutation, which in turn results into intensive functional evaluation. PSO, on the other hand; is reported as an efficient algorithm in terms of its fast convergence speed. The reason behind this strength is the application of simple mathematical operator instead of intense evolutionary operators. Besides the efficiency of swam intelligence, its effectiveness is found to be constrained because of its pre-mature convergence and lack of diversity. This creates a pressing need to devise an algorithm which is effective and likely efficient.

In the literature, researchers have proposed numerous variants of GA and swam intelligence to handle the convergence speed and pre-mature convergence issues respectively. Specifically, the variants of GA include but not limited to, genetic programming [5], evolution strategies [6], differential evolution [7], and paddy field algorithm [8] etc. In these approaches a significant improvement has been reported in terms of its effective convergence. However, marginal improvements have been reported to handle the convergence speed issue. Likewise, the researchers have proposed numerous variants of swam intelligence such as PSO [9], ant colony optimization [10], artificial bee colony algorithm [11], fish swarm algorithm [12], intelligent water drops algorithm [13], bacterial foraging optimization algorithm [14], artificial immune system algorithm [15], firefly algorithm [16], group search optimizer [17], and shuffled frog leaping algorithm [18] etc. These swam intelligence have a notable improvement in convergence speed but, a marginal development is being observed in the pre-mature convergence issue. In these approaches, PSO has been reported as relatively better candidate as swam based optimization approach. The above facts create a rationale to hybrid both GA and PSO for effective convergence and good convergence speed [19].

Researchers have devised numerous hybrid genetic particle swarm optimization (HGPSO) algorithms for a variety of applications. This includes, but not limited to, cost optimization of an off-grid hybrid energy system [19], path planning for mobile robots [20], QoS guaranteed intelligent routing [21], antenna design [22], low exhaust emission diesel engine design [23] etc. These numerous HGPSO algorithms can be broadly classified into three major types. The functional description of these three types is as follows [19, 24]:

1. In HGPSO-I, the *gbest* particle does not change its position over some designated time steps. Also, the crossover operation is performed on *gbest*particles with chromosomes of GA.
2. In HGPSO-II, the stagnated pbest particles change their positions by mutation operator of GA.
3. In HGPSO-III, the total numbers of iterations are equally shared by GA and PSO algorithms. In this model, both GA and PSO algorithms are run in parallel.

In this paper, a new hybrid scheme of GA and PSO is presented. The proposed hybrid scheme has been tested on various benchmark test functions for global optimization. Out of many test functions, three functions and their results are presented here. These test functions are Ackley function, Bird function and Egg crate function. The simulation results prove that the proposed HGPSO not only outperform GA and PSO but it is far better than the existing three HGPSO mentioned in the literature [19, 24].

II. Proposed Hybrid Algorithm

This section presents the structure and description of proposed HGPSO. The functional flow of the proposed algorithm is illustrated in Fig.1. In this figure, both pbest and gbest update in parallel. If the updated values of pbest and gbest satisfy the condition to stop, the update process terminates; else it proceeds to map swam onto chromosomes. Subsequently, new chromosomes generate, cross over and mutate. These chromosomes re-map onto the swam to evaluate if the pbest is stagnant. The mutation occurs only if the pbest is stagnant else the flow proceeds to update the pbest and gbest with the new population.

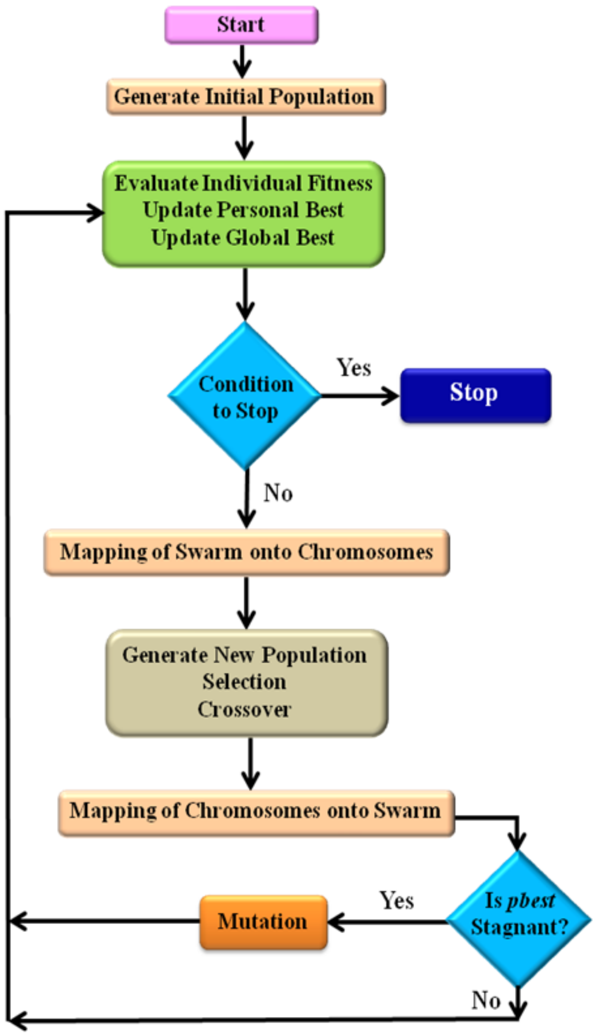

Fig. 1: Flowchart of proposed HGPSO

III. Benchmark Test Functions

There are numerous benchmark test functions presented in the literature to evaluate heuristic optimization algorithms [25]. These functions have different domain and range boundaries and distinct mathematical properties. Following three benchmark test functions have been used to evaluate the proposed HGPSO in comparison with GA, PSO, HGPSO-I, HGPSO-II and HGPSO-III algorithms.

A. Ackley Function

This function has the characteristics of continuity, differentiability, non-separabilty, scalability and multimodality [25]. The mathematical expression of the function is

$$f_1(x) = -20e^{-0.02\sqrt{D^{-1}\sum_{i=1}^{D} x_i^2}} - e^{D^{-1}\sum_{i=1}^{D}\cos(2\pi x_i)} + 20 + e \qquad (1)$$

The search region is $-35 \le x_i \le 35$. The global minimum exists at multimodal origin. Mathematically it is represented as $x^* = f(0, 0, \ldots\ldots, 0)$, and the value of minima is $f(x^*) = 0$. The characteristic curve of Ackley function is shown in Fig. 2.

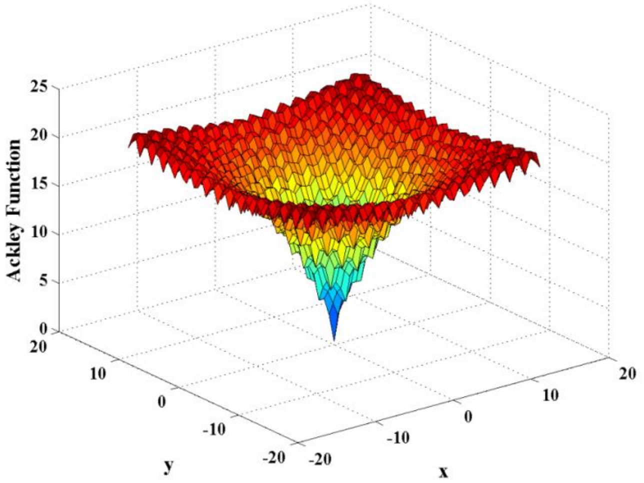

Fig. 2: The Ackley function

B. Bird Function

The Bird function is continuous, differentiable, non-separable, scalable and multimodal [25]. The mathematical expression of the function is

$$f_2(x) = \sin(x_1)e^{[1-\cos(x_2)]^2} + \cos(x_2)e^{[1-\sin(x_1)]^2} + (x_1 - x_2)^2 \qquad (2)$$

The search region is $-2\pi \le x_i \le 2\pi$. The global minimum is located at $x^* = (4.70104, 3.15294), (-1.58214, -3.13024)$ and the minimum function value is $f(x^*) = -106.764537$. The characteristic curve of Bird function is shown in Fig. 3.

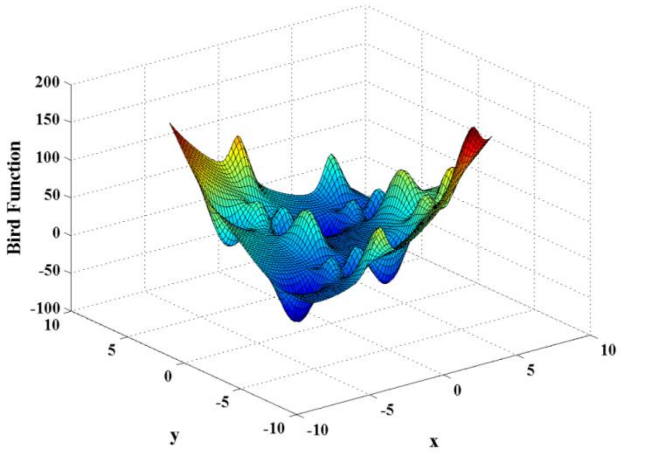

Fig. 3: The Bird function

C. Egg Crate Function

The Egg Crate function is continuous, separable, non-scalable and multimodal [25]. The mathematical relation of the function is

$$f_3(x) = x_1^2 + x_2^2 + 25\left(\sin^2(x_1) + \sin^2(x_2)\right) \quad \mathbf{(3)}$$

The search region is $-5 \le x_i \le 5$. The global minimum is located at $x^* = f(0,0)$ and the function is $f(x^*) = 0$. The characteristic curve of Egg Crate function is shown in Fig. 4

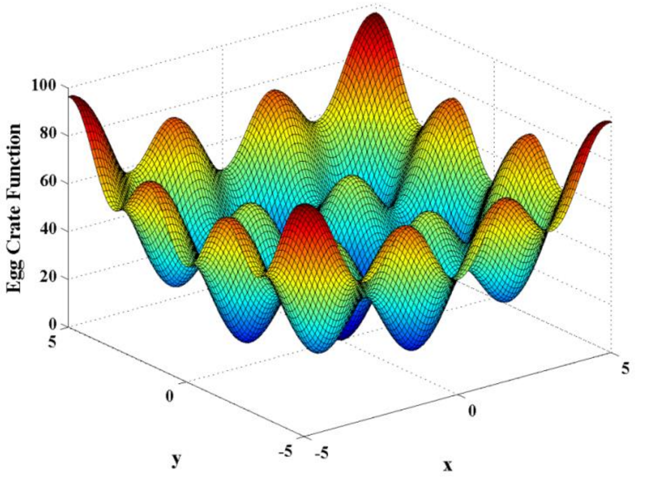

Fig. 4: The Egg Crate function

IV. Simulation Results and Discussion

The proposed HGPSO has been tested through above three benchmark test functions mentioned in section 3. In addition; GA, PSO, HGPSO-I, HGPSO-II and HGPSO-III algorithms have also been tested through the same test functions in order to compare the performance of the proposed algorithm.

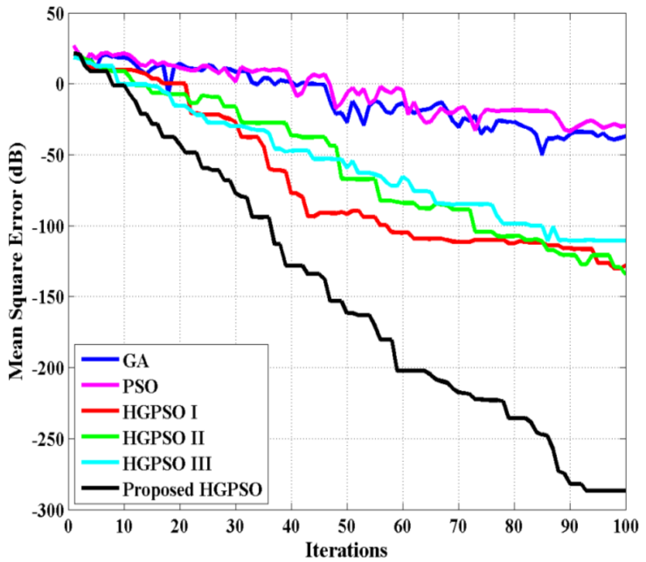

Fig. 5: The MSE of GA, PSO, HGPSO-I, HGPSO-II, HGPSO-III and proposed HGPSO using Ackley function

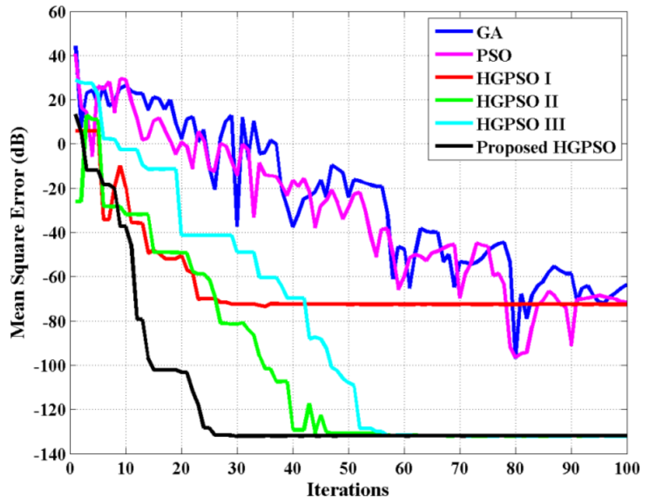

Fig. 6: The MSE of GA, PSO, HGPSO-I, HGPSO-II, HGPSO-III and proposed HGPSO using Bird function

Figures 5, 6 and 7 are the plots of mean square error (MSE) obtained by testing the heuristic algorithms of GA, PSO, HGPSO-I, HGPSO-II, HGPSO-III and the proposed HGPSO on the standard benchmark functions of Ackley, Bird and Egg Crate respectively. The figures show that all the heuristic algorithms satisfy the three standard functions within the given domain; however the proposed HGPSO outperforms all the other existing heuristic approaches. The proposed algorithm not only proves to be the best in terms of convergence speed but it has the least mean square error while approaching the global optimum value of the three test functions.

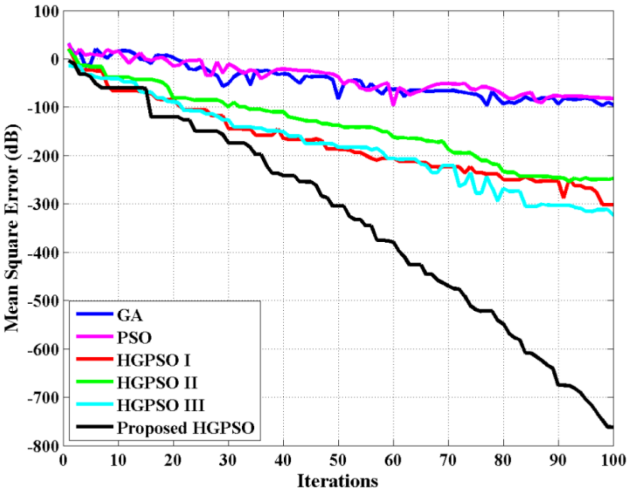

Fig. 7: The MSE of GA, PSO, HGPSO-I, HGPSO-II, HGPSO-III and proposed HGPSO using Egg Crate function

V. Conclusion

A novel hybrid heuristic algorithm of GA and PSO (HGPSO) has been proposed and tested on three standard benchmark test functions namely Ackley, Bird and Egg Crate. The results show that the proposed algorithm has much better performance as compared to existing GA, PSO, HGPSO-I, HGPSO-II and HGPSO-III. The proposed algorithm has the lowest convergence time and the lowest value of mean square error (MSE) than all the existing heuristic approaches under consideration.

References

[1] D.B. Fogel, Evolutionary Computation: Toward a New Philosophy of Machine Intelligence, IEEE Press, Piscataway, NJ, 1995.

[2] X. Yao (Ed.), Evolutionary Computation: Theory and Applications,World Scientific, Singapore, 1999.

[3] M. Zubair (2014) Design and Optimization of Antenna for MIMO Systems via Heuristic Algorithms. PhD thesis, IQRA University, Karachi.

[4] Hussain, Syed Sajjad, Manzoor Hashmani, and Kamran Raza. "Comparison of Optimized Image Retrieval Methods Based on Color and Texture Features." Sindh University Research Journal-SURJ (Science Series) 45.3 (2013).

[5] Koza, John R. 1992. Genetic Programming: On the Programming of Computers by Means of Natural Selection. Cambridge, MA: The MIT Press

[6] Beyer, H.G. and Schwefel, H.P. 2002: Evolution strategies. Natural Computing 1,3–52.

[7] R. Storn, K. Price, Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces, Journal of Global Optimization 11 (1997) 341–359.

[8] Upeka Premaratne , Jagath Samarabandu, and Tarlochan Sidhu, ―A New Biologically Inspired Optimization Algorithm‖,Fourth International Conference on Industrial and Information Systems, ICIIS 2009,28-31 December 2009, Sri Lanka.

[9] Kennedy, J.; Eberhart, R. (1995). "Particle Swarm Optimization". Proceedings of IEEE International Conference on Neural Networks. IV. pp. 1942–1948.

[10] Dorigo, M., Maniezzo, V., & Colorni, A. (1996). Ant System: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics – Part B, 26, 29–41.

[11] D. Karaboga, B. Basturk, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm, Journal of Global Optimization 39 (2007) 459–471

[12] X. Li, Z. Shao, J. Qian,Anoptimizing method base on autonomous animates: fish- swarm algorithm, Systems Engineering Theory and Practice 22 (2002) 32–38.

[13] Shah_Hosseini, H. Shahid Beheshti Univ., Tehran Problem solving by intelligent water drops IEEE Congress on Evolutionary Computation, 2007. CEC 2007.

[14] K. M. Passino, ―Biomimicry of bacterial foraging for distributed optimization and control, IEEE Control Syst. Mag., vol. 22, no. 3, pp.52–67, Jun. 2002

[15] D. Dasgupta, Artificial Immune Systems and Their Applications, Springer, Berlin, 1999

[16] X.S Yang, ―Fire fly algorithm for multimodal optimization‖,in proceedings of the stochastic Algorithms. Foundations and Applications(SAGA 109) vol.5792of Lecture notes in Computer Sciences Springer,Oct.2009

[17] S.He,Q.H.Wu, Senior Member IEEE and J.R Saunders.A novel group search optimizer inspired by Animal Behavioral Ecology;2006,IEEE Congress on Evolutionary Computation,1272-1278

[18] Eusuff MM and K.E Lansey; Optimization of water distribution network design using SFLA(2003)

[19] Deepali Sharma, Prerna Gaur & A. P. Mittal (2014) Comparative Analysis of Hybrid GAPSO Optimization Technique With GA and PSO Methods for Cost Optimization of an Off-Grid Hybrid Energy System, Energy Technology & Policy, 1:1, 106-114, DOI: 10.1080/23317000.2014.969450

[20] Huang, Hsu-Chih. "FPGA-based hybrid GA-PSO algorithm and its application to global path planning for mobile robots." Przeglad elektrotechniczny 88.7B (2012): 281-284.

[21] Sarasvathi, V., N. C. S. N. Iyengar, and Snehanshu Saha. "QoS Guaranteed Intelligent Routing using Hybrid PSO-GA in Wireless Mesh Networks". Cybernetics and Information Technologies 15.1 (2015): 69-83.

[22] Li, Wen-Tao, Le Xu, and Xiao-Wei Shi. "A hybrid of genetic algorithm and particle swarm optimization for antenna design." PIERS online 4.1 (2008): 56-60.

[23] S. Jeong , S. Obayashi & Y. Minemura (2008) Application of hybrid evolutionary algorithms to low exhaust emission diesel engine design, Engineering Optimization, 40:1, 1-16, DOI: 10.1080/03052150701561155

[24] Kao, Y.-T.; Zahara, E. A Hybrid Genetic Algorithm and Particle Swarm Optimization for Multimodal Functions. In Applied Soft Computing 8; Elsevier, 2008, pp 849–857. doi:10.1016/j.asoc.2007.07.002.

[25] M. Jamil and X. S. Yang, "A Literature Survey of Benchmark Functions For Global Optimization Problems" Int. Journal of Mathematical Modelling and Numerical Optimisation, Vol. 4, No. 2, pp. 150–194 (2013). DOI: 10.1504/IJMMNO.2013.055204

Authors:

Muhammad Zubair zubair@iqra.edu.pk
Jawwad Ahmad jawwad@iqra.edu.pk
Syed Sajjad Hussain Rizvi shrizvi@iqra.edu.pk
FEST Department
Main Campus, Iqra University, Pakistan

Muhammad Moinuddin mmsansari@kau.edu.sa
Electrical & Computer Engineering Department,
King Abdulaziz University, Saudi Arabia