©2022 International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies

ISSN 2228-9860 eISSN 1906-9642 CODEN: ITJEA8

TuEngr Group

International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies

http://TuEngr.com

A Hybrid New Gravitational Coefficient Function of Gravitational Search Algorithm with Mutation for Search Performance

Pattrawet Tharawetcharak[1*], Aumnad Phdungsilp[1], Suparatchai Vorarat[1]

[1] *Graduate Program in Engineering Management, College of Innovative Technology and Engineering, Dhurakij Pundit University, Bangkok, THAILAND.*

**Corresponding Author (Email: 637191120002@dpu.ac.th).*

Paper ID: 13A1J

Volume 13 Issue 1

Received 09 August 2021

Received in revised form 24 October 2021

Accepted 05 November 2021

Available online 15 November 2021

Keywords:

Gravitational Search Algorithm (GSA); Mutation; Search Performance; Benchmark Function.

Abstract

This paper proposes a hybrid New Gravitational Coefficient Function of Gravitational Search Algorithm with Mutation (NGCFGSAM). Since most of the hybrid algorithms have been concerned with the search performance of the solution. This study investigates the features that influence the algorithm on global search performance. The novel hybrid algorithm is compared to previous functions in the literature based on six benchmark functions, including both unimodal landscape functions and multimodal landscape functions. The experimental results are shown that the proposed NGCFGSAM outperforms the conventional benchmark functions. The proposed hybrid algorithm worked well on multimodal landscape functions. Better solutions compensate for the slower convergence rate by balancing the exploration and exploitation phases. For future work, studies on the investigation and rigorously prove the parameter turning for convergence rate. More benchmark functions and more algorithm comparison tests should be investigated.

Disciplinary: Optimization, Engineering Management.

Cite This Article:

Tharawetcharak, P., Phdungsilp, A., and Vorarat, S. (2022). A Hybrid New Gravitational Coefficient Function of Gravitational Search Algorithm with Mutation for Search Performance. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies, 13*(1), 13A1J, 1-12. http://TUENGR.COM/V13/13A1J.pdf DOI: 10.14456/ITJEMAST.2022.10

1 Introduction

The Gravitational Search Algorithm (GSA) is a popular metaheuristic in evolutionary algorithms (Rashedi et al., 2009). The algorithm's concept is based on the Newtonian law of motion, which is "every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them" (Rashedi et al., 2007). The search solution of GSA is stated from the population. Each solution is represented as an agent that has mass, position, and velocity. The gravitational force of each agent is calculated according to Newton's universal law of velocity. The gravitational constant of each agent is calculated according to Newton's law motion with attracted by the gravitational force (Yin et al., 2018). In the literature, there are a number of studies related to succeeding GSA in many applications such as robot path planning (Das et al., 2016), energy and renewable energy management (Saravanan and Srinivasan, 2016; Packiasudha et al., 2017), logistics management (Hosseinabadi et al., 2016), transportation problem (Sosa and Dhodiya, 2020), economic load dispatch problem (Santra et al., 2021), and data analysis (Dowlatshahi and Nezamabadi-pour, 2014). However, these studies have not been able to search for complex optimization problems.

Furthermore, GSA has been improved to cope with specific problems and for better search performances in unimodal landscape functions. Researchers have improved so-called the New Gravitational Coefficient Function of GSA (NGCFGSA) for enhancing gravitational search algorithm's efficiency and convergence rate performance (Tharawetcharak et al., 2019) and the GSA based on chaotic local search to promote the algorithm's local search ability (Guo et al., 2021). There is also a study on hybrid algorithms by artificial grasshopper optimization and meta-heuristic algorithm for improving the exploitation and exploration search to solve discover global optimum in given search space (Dahiya et al., 2019). To solve the problem of green-based partner selection, Xiao et al. (2016) combined the GSA and Particle Swarm Optimization (PSO) to improve the problem-solving performance. The improved method is classified as a hybridization technique because it employs a co-evolutionary technique of PSO to GSA known as I-GSA/PSO. Computational experiments revealed that I-GSA/PSO produced better solutions than other competitors, particularly on conventional GSA and PSO. Nonetheless, these studies did not discuss the advantages of their improved methods over traditional GSA. Yin et al. (2018) proposed the GSA with crossover operation. The proposed method developed the performance of the crossover technique to explore the global optimization method and to promote the algorithm's performance. Experimentally, the algorithm outperformed other optimization approaches in various tests and is appropriate for dealing with complex optimization problems.

Based on the above literature, this study focuses on improving the search performance of algorithms for unimodal and multimodal landscape functions. Even there are a number of fancy GSA variants. This paper investigates the impact and performance of a hybrid GSA with a GA by a specific selected mutation method of GA. Thus, this study proposes a hybrid New Gravitational Coefficient Function of Gravitational Search Algorithm with Mutation (NGCFGSAM) for search performance. The contribution of this paper is the development of a novel hybrid algorithm for search performance. This paper is organized as follows: Section II describes the conventional GSA and GA. The paper has described the idea of this novel hybrid algorithm in Section III. Section IV presents parameter fine-tuning and illustrates the performance of the proposed novel hybrid algorithm by computational experiment. The results are compared and discussed in Section V. Finally, the conclusion is described in Section VI.

2 Literature Review

This section describes the principle of GSA and GA. GSA is a population-based stochastic search, and the swarm algorithm (Rashedi et al., 2009). The method is based on Newton's laws of motion. As mentioned earlier that Newton's law states that every particle (mass) attracts another particle via gravitational force. Technically, each particle in GSA has four characteristics, including particle position, inertial mass, active gravitational mass, and passive gravitational mass. The position of a particle provides the solution to a problem, whereas the fitness function calculates the gravitational and inertial masses (Kumar and Sahoo, 2014). Based on the GSA literature such as Rashedi et al. (2009), the conventional gravitational coefficient function ($G(t)$) is a decreasing function as shown in Eq. (1),

$$G(t) = G(t_0) \times \left(\frac{t_0}{t}\right)^{\beta}, \beta < 1 \quad (1),$$

where $G(t_0)$ is the gravitational constant value at the first cosmic quantum-interval of time t_0. $G(t)$ is the gravitational constant value at time t (Mansouri et al., 1999). The equation is an increasing function of t and depends on the value of β. Figure 1 shows the values of $G(t)$ when t is varied for the conventional gravitational coefficient function, which observes the convergence behavior of the optimal fast value. However, the conventional one tends to be premature. It could not do the exploitation phase considerably.

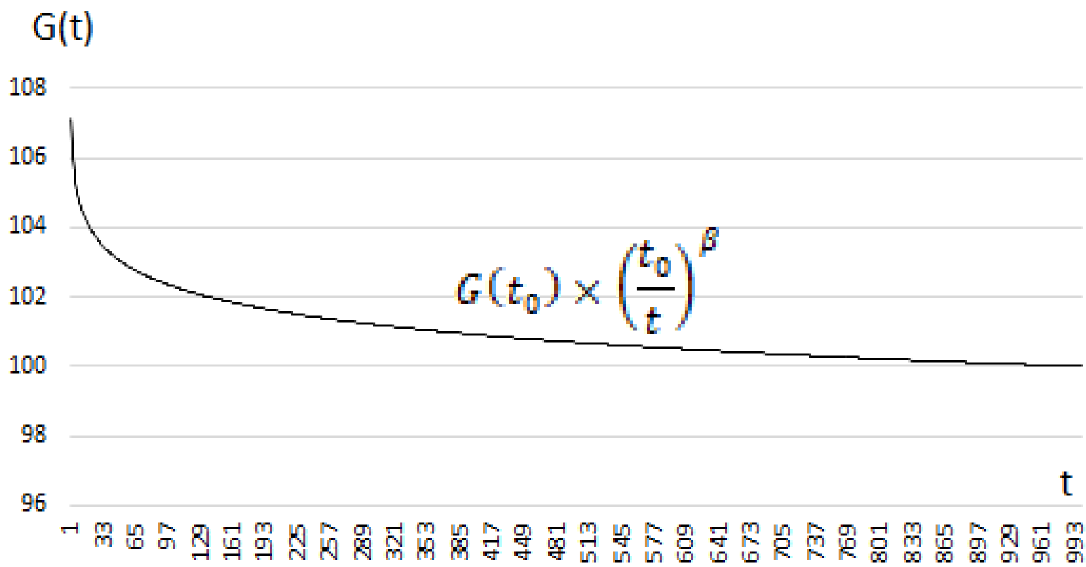

Figure 1: $G(t)$ value of the conventional function.

Thereafter, researchers have developed the New Gravitational Coefficient Function of GSA (NGCFGSA) as shown in Eq. (2) and Figure 2. The NGCFGSA can search global optimization for unimodal landscape function, which deploys an exponential function based on the conventional gravitational coefficient function (Tharawetcharak et al., 2019). According to Figure 2, the advantages of convergence behavior for one could exploit the search satisfactorily. Thus, $G(t_0)$ of the NGCFGSA could conduct the fine search and yield a better solution continuously. Therefore, this paper is interested in hybrid NGCFGSA with mutation method in GA to search global optimization for multimodal landscape function.

$$G(t) = G(t_0)exp^{(\frac{t}{T})^{\beta}} \quad (2),$$

where t is the current iteration number, T is the maximum iteration number, and β is the constant value number.

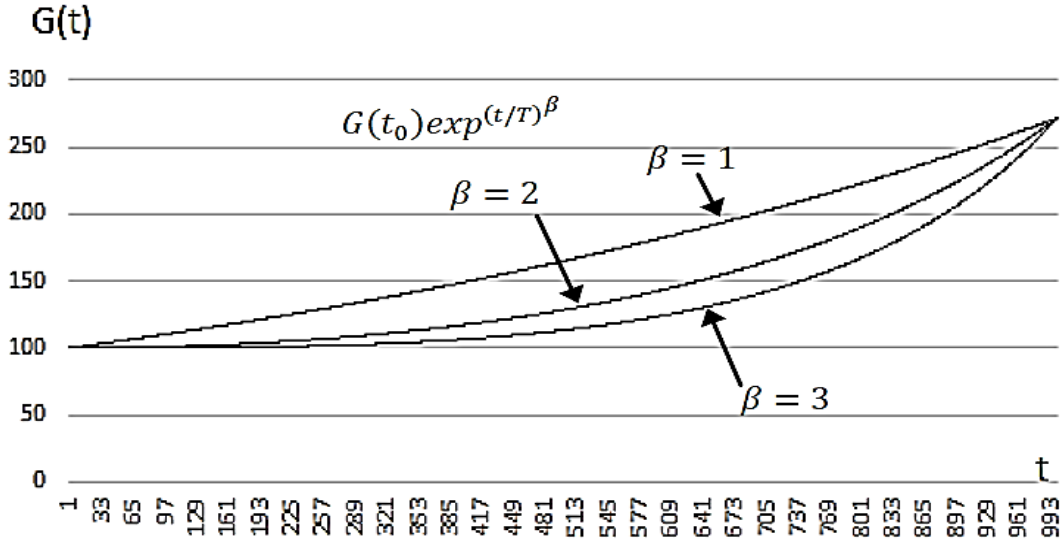

Figure 2: $G(t)$ value of NGCFGSA.

GA is an optimization algorithm influenced by natural selection. It is a population-based search method that employs the survival of the fittest idea (Michalewicz, 1992). The new populations are created by iteratively applying genetic operators to individuals already present in the population. The chromosome representation of GA includes chromosomal representation, selection, crossover, mutation, and fitness function computation (Michalewicz and Schoenauer, 1996). The first step of GA in the implementation is to compute an initial population. The algorithm is a family of search methods inspired by evolution (Whitley, 1994). It encodes a likely solution to a problem on easy chromosomes data, and crossover and mutation operators to these algorithms to conserve information (Premalatha and Natarajan, 2009). Technically, each population in GA has four methods for the operator during the search process, including encoding, selection, crossover, and mutation (Katoch et al., 2021).

The most prevalent encoding method of GA is the binary encoding technique. Each gene or chromosome is represented by a 1 or 0 string. Each bit in binary encoding conveys the solution's properties. It allows for more rapid implementation of crossover and mutation operators. However, converting to binary needs more effort and the correctness of the process is dependent on the binary conversion. The bitstream is modified in response to the issue. Because of epistasis and natural representation, the binary encoding technique is inappropriate for several engineering design challenges (Katoch et al., 2021).

The selection method of GA is a crucial phase in GA. The selection determines whether or not a certain string will participate in the reproduction process. The reproduction operator is another name for the selection process. The pace of convergence of GA is determined by the selection pressure, such as Roulette wheel selection, Rank selection, Tournament selection, Boltzmann selection, and Stochastic Universal Sampling, which are some well-known selection approaches (Jebari and Madiafi, 2013; Katoch et al., 2021).

The crossover method is an operator that combines the genetic information of two or more parents to produce offspring. The most well-known crossover methods are single-point, two-point, k-point, uniform, partially matched, order, precedence preserving crossover, shuffle, reduced surrogate, and cycle (Fox and McMahon, 1991; Katoch et al., 2021).

The next important step, the mutation method is an operator that preserves genetic variability from one population to the next. The most well-known mutation methods are displacement, simple inversion, and scramble mutation. The displacement mutation method displaces a substring of a given individual solution within itself. The position for displacement is picked at random from the specified substring so that the final solution is legitimate as well as a random displacement mutation. There are two types of displacement mutation variants: exchange mutation and insertion mutation. In the exchange mutation and insertion mutation operators, a portion of an individual solution is either swapped with another portion or inserted in a different spot (Jebari and Madiafi, 2013; Katoch et al., 2021). The mutation method is an inversion operator that also reverses a randomly chosen string and places it in a randomly chosen location, which is an interesting method.

3 The Proposed Hybrid Algorithm

This paper is interested in the efficiency of the new gravitational coefficient ($G(t)$), as shown in Eq. (2). According to the previous studies, various researchers have introduced the concept of the NGCFGSA that varied over time and demonstrated its performance through computational experiments (Tharawetcharak et al., 2019). This paper contributes to the literature by integrating the advantages of NGCFGSA with the advantages of GA in the mutation method. The literature review found that the NGCFGSA as shown in Equation (2) can search global optimization for unimodal function, which deploys an exponential function based on the conventional gravitational coefficient function (Tharawetcharak et al., 2019). Therefore, the proposed algorithm in this paper is the proposed hybrid gravitational search algorithm using NGCFGSA with mutation. Moreover, the proposed algorithm can be search performance with both unimodal and multimodal landscape function perfectly. Figure 3 presents the process flow, and the step-by-step procedure for NGCFGSAM is given as

Step 1: Identification of search space.

Step 2: Generate the initial population.

Step 3: Evaluate the fitness function for each particle in the population.

Step 4: Update the gravitational coefficient value by using NGCFGSA.

$$G(t) = G(t_0)exp^{(\frac{t}{T})^{\beta}}$$

$$Best(t) = \min_{i\in\{1,\ldots,N\}} Fit_i(t)$$

$$Worst(t) = \max_{i\in\{1,\ldots,N\}} Fit_i(t)$$

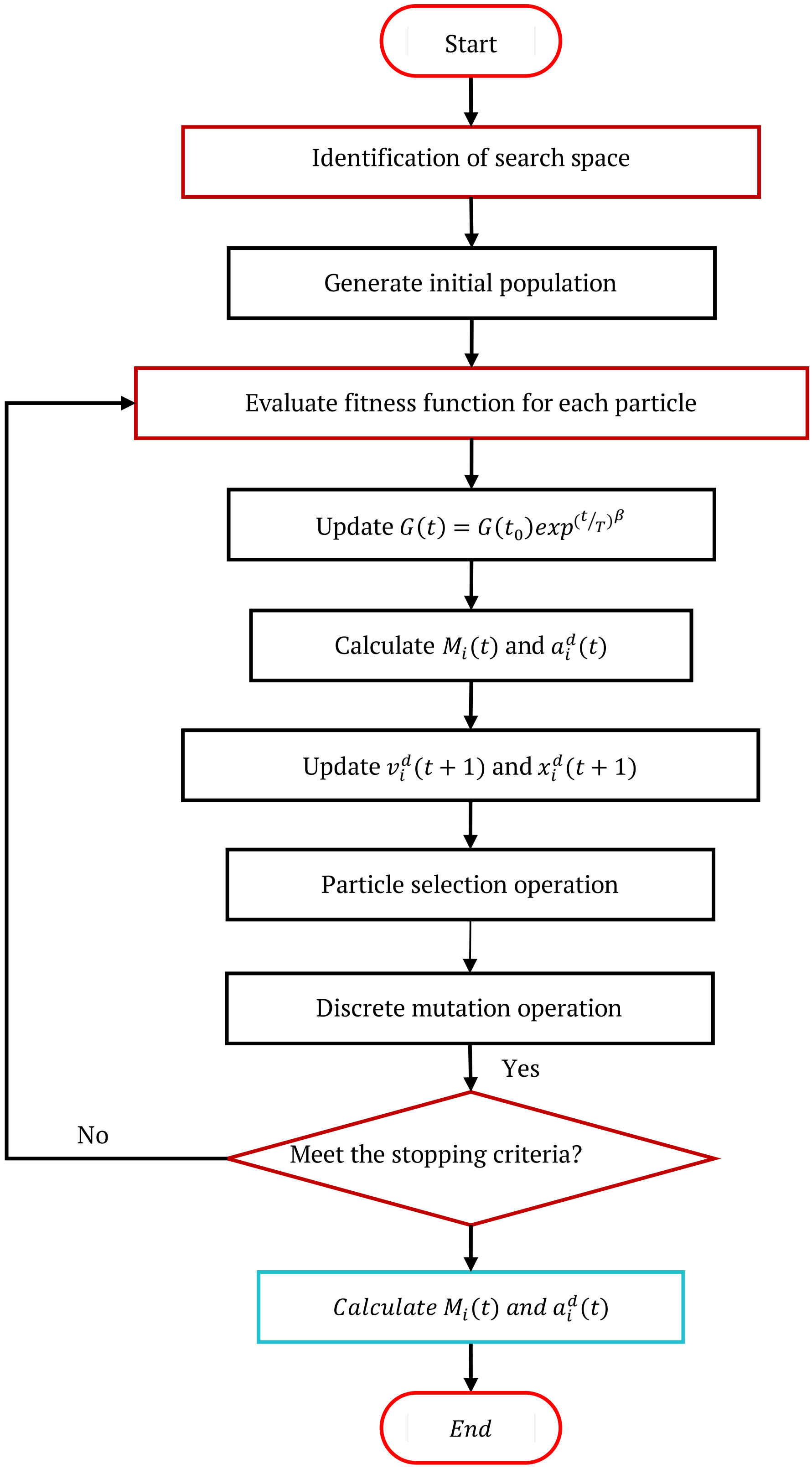

Figure 3: The procedure of NGCFGSAM.

Step 5: Calculate the total force in different direction value at time t $(M_i(t))$, and $(a_i^d(t))$ is acceleration value at time t. Where M_{aj} is the active gravitational mass related to agent j, ε is a small constant, R_{ij} is the Euclidian distance between agent i and j, and $rand_j$ is a uniform random variable in the interval [0,1].

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_i(t)}, \text{ where } m_i = \frac{Fit_i(t) - Worst(t)}{Best(t) - Worst(t)}$$

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ij}(t)}, \text{ where } F_i^d(t) = \sum_{j=1, i\neq j}^{N} rand_j F_{ij}^d(t) \text{ and}$$

$$F_{ij}^d(t) = G(t)\frac{M_{aj}(t)}{R_{ij}(t)+\varepsilon}\left(x_j^d(t) - x_i^d(t)\right)$$

Step 6: Update the particle velocity and position. The velocity and position of a particle are calculated by the following equations. Where $v_i^d(t+1)$ is the particle velocity value at time t, $x_i^d(t+1)$ is the particle position value at time t, and $rand_i$ is a uniform random variable in the interval [0,1].

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t),$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1),$$

Step 7: Particle selection operation of two particles in the population of position without repetition, according to their fitness values.

Step 8: Discrete mutation operation of each particle in the population.

Step 9: Repeat step 3 through step 8 until the stopping criteria are met.

4 Computational Experiments

The computational experiments were conducted to validate the performance of the proposed hybrid algorithm based on the NGCFGSAM (details see Figure 3). The numerical experiments were simulated based on six nonlinear benchmark functions, including unimodal and multimodal optimization problems. The unimodal landscape function consists of Sphere, Matyas, and Rosenbrock while the multimodal landscape function includes Griewank, Schwefel, and Ackley. For the computation, the proposed hybrid algorithm and all hybrid algorithms were written in Matlab version r2016a and simulated on PC with Intel Core i5-8250U CPU @ 1.80 GHz processor and 8 GB RAM for testing the proposed hybrid algorithm.

The study began with a review of parameter settings from the literature and then conducted preliminary experiments. For the conventional $G(t)$ function, the setting was t_0 = 1000, β = 0.01, and $G(t_0)$ = 100. For the new $G(t)$ function, the setting was T = 1000, β = 2, and $G(t_0)$ = 100 (Rashedi et al., 2009; Tharawetcharak et al., 2019). In addition, the number of agents N was 50. Because the GSA is a stochastic searching technique. It runs each combination of experiments for 30 independents to eliminate random discrepancy for six benchmark functions in the literature (Rashedi et al., 2009; Tharawetcharak et al., 2019). Theoretically, it is challenging to find globally optimal solutions for multimodal landscape functions. Furthermore, it is determined by the search's starting point. The starting points in this study are generated randomly. Tables 1 and 2 show the complex formula of the functions, the search space boundary, and their optimal solutions for the benchmark functions. Figures 4 to 9 present the dimensional landscape in relation to the benchmark functions used in this study.

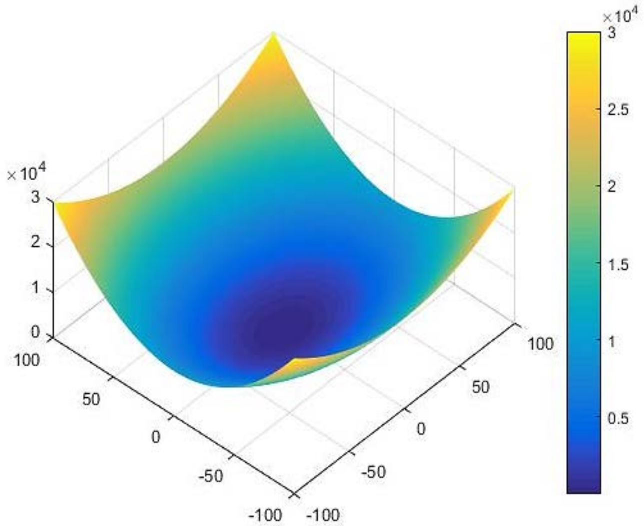

Figure 4: Sphere function.

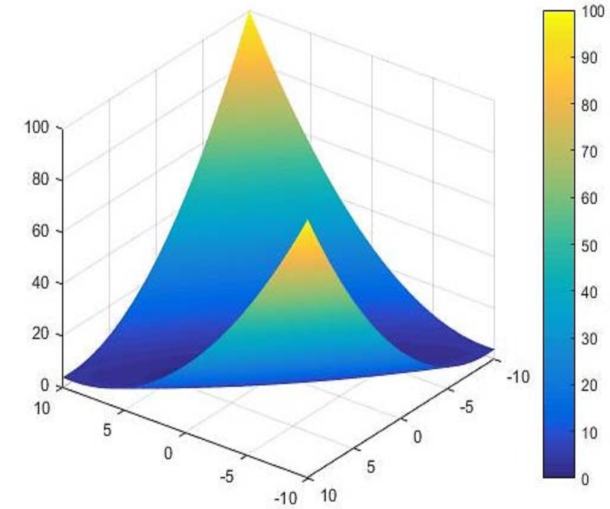

Figure 5: Matyas Function.

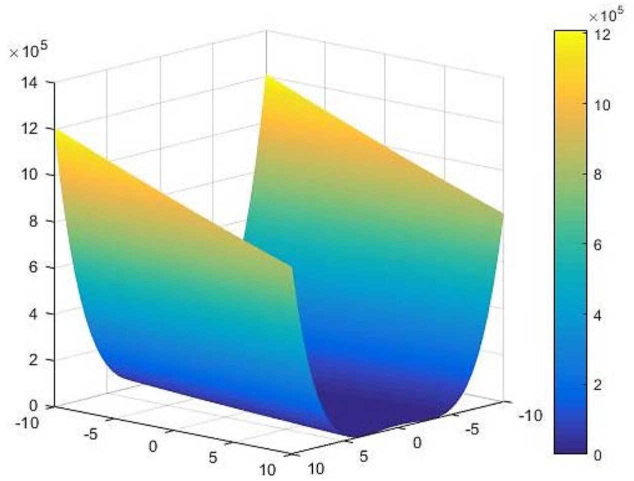

Figure 6: Rosenbrock function.

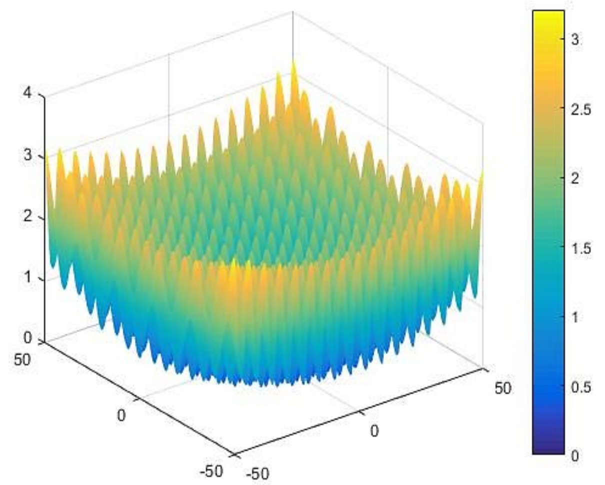

Figure 7: Griewank function.

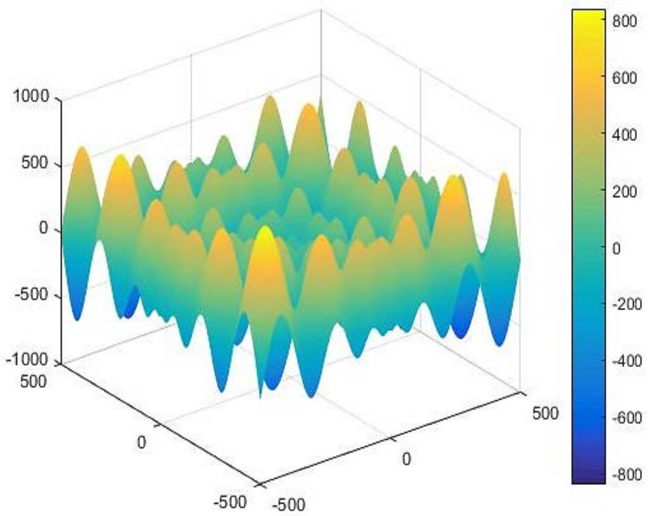

Figure 6: Rosenbrock function.

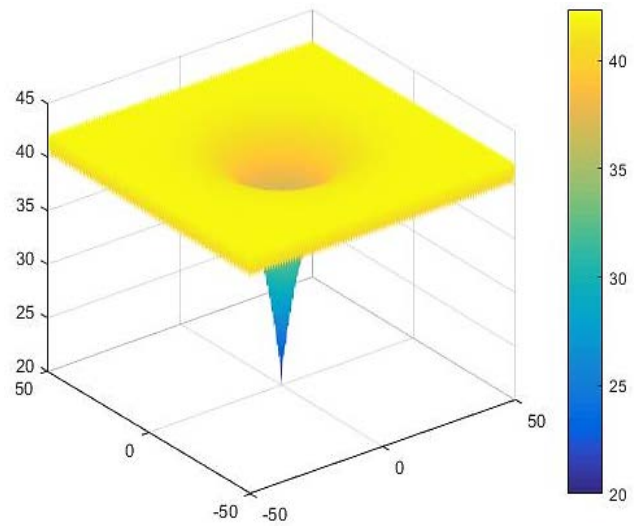

Figure 7: Griewank function.

Table 1: Test Functions Name

Function name	Description	Search Range
Sphere	$f(X)=\sum_{i=1}^{d} x_i^2$	$[-100,100]^d$
Matyas	$f(X)=0.26(x_1^2+x_2^2)-0.48x_1x_2$	$[-10,10]^d$
Rosenbrock	$f(X)=100(x_2-x_1^2)^2+(1-x_1)^2$	$[-10,10]^2$
Griewank	$f(X)=\sum_{i=1}^{d}\frac{x_i^2}{4000}-\prod_{i=q}^{d}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	$[-600,600]^d$
Schwefel	$f(x)=418.9829d-\sum_{i=1}^{d} x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)$	$[-500,500]^d$
Ackley	$f(X)=-20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d}x_i^2}\right)-\exp\left(\frac{1}{d}\sqrt{\frac{1}{d}\sum_{i=1}^{d}\cos(2\pi x_i)}\right)+20+\exp(1)$	$[-32.768,32.768]^d$

Table 2: Optimal Solutions of The Test Functions Name

Function name	Optimal Solution	
	$f(X^*)$	X^*
Sphere	0	$(0,\dots,0)$
Matyas	0	$(0,0)$
Rosenbrock	0	$(1,\dots,1)$
Griewank	0	$(0,\dots,0)$
Schwefel	0	$(420.9687,\dots,420.9687)$
Ackley	0	$(0,\dots,0)$

5 Results and Discussion

This section describes the experiment results and statistical tests of computational experiments. Table 3 summarizes the test results in terms of mean optimal solutions and their standard deviations. The best results of NGCFGSAM for each benchmark function are underlined. As shown in Table 3, the proposed algorithm outperforms the six benchmark functions. The NGCFGSAM produced results closer to the optimal solution for both unimodal landscape function and multimodal landscape functions. Additionally, it also resulted in a lower level of uncertainty. This means that the proposed algorithm is more trustworthy on the search path. Because results are subject to uncertainty. Therefore, the study cannot claim that the proposed hybrid algorithm is superior to the conventional algorithms. A one-way ANOVA analysis was employed to perform a statistical test (Kim, 2017).

Table 3: Minimization experiment results of benchmark function

Function name	Minimization result	Algorithms			
		GA	GSA	NGCFGSA	NGCFGSAM
Sphere function	Average mean fitness	6.3×10^{-11}	7.3×10^{-11}	9.7×10^{-17}	4.8×10^{-17}
	Average best-so-far	6.2×10^{-11}	7.1×10^{-11}	4.8×10^{-17}	4.7×10^{-17}
Matyas Function	Average mean fitness	$5.6 \times 10^{+3}$	$0.16 \times 10^{+3}$	$0.15 \times 10^{+3}$	$0.95 \times 10^{+2}$
	Average best-so-far	$5.6 \times 10^{+3}$	$0.15 \times 10^{+3}$	$0.12 \times 10^{+3}$	$0.95 \times 10^{+2}$
Rosenbrock function	Average mean fitness	$1.1 \times 10^{+3}$	$0.25 \times 10^{+2}$	$0.23 \times 10^{+2}$	$0.21 \times 10^{+2}$
	Average best-so-far	$1.0 \times 10^{+3}$	$0.25 \times 10^{+2}$	$0.22 \times 10^{+2}$	$0.19 \times 10^{+2}$
Griewank function	Average mean fitness	1.16	0.29	1.32	0.08
	Average best-so-far	1.14	0.04	1.31	0.02
Schwefel function	Average mean fitness	$-1.2 \times 10^{+4}$	$-2.8 \times 10^{+3}$	$-3.1 \times 10^{+3}$	$-3.0 \times 10^{+3}$
	Average best-so-far	$-1.2 \times 10^{+4}$	$-2.6 \times 10^{+3}$	$-2.7 \times 10^{+3}$	$-2.7 \times 10^{+3}$
Ackley function	Average mean fitness	2.16×10^{-4}	6.9×10^{-6}	3.5×10^{-5}	4.8×10^{-6}
	Average best-so-far	2.13×10^{-4}	6.9×10^{-6}	3.5×10^{-5}	4.8×10^{-6}

The metaheuristics approaches are based on a stochastic search strategy and their results are varied and determined by chance. Accordingly, a statistical method was used to perform a systematic performance verification. The one-way ANOVA analysis with α=0.05 was applied for the statistic test. This is due to there being only one factor for each tested NGCFGSAM. The research hypothesis is given as

H_1: Minimization result of the proposed NGCFGSAM algorithm is less than conventional algorithms (GA, GSA, NGCFGSA).

Using a statistics software package on Microsoft Excel 2019 MSO (Version 2110 Build 16.0.14527.20270) 64-bit for hypothesis testing, the study discovered that the proposed hybrid algorithm differs significantly from benchmark functions. Table 4 presents the test values and decisions. According to Table 4, this study could claim that the proposed NGCFGSAM enhances the performance, better than the conventional algorithms (thus H_1 is accepted (p-value less than 0.05)).

Table 4: Statistical test analysis (One-way ANOVA)

Algorithms	*SS*	*df*	*MS*	*F*	*p-value*	*F crit*
Between Groups	1.107×10^{8}	5	2.214×10^{7}	4.72	0.0063	2.773
Within Groups	8.452×10^{7}	18	4.696×10^{6}			
Total	1.952×10^{8}	23				

6 Conclusion

This paper proposed a hybrid algorithm based on the search performance phases of the latest NGCFGSA. The study used a mutation method of GA hybridized NGCFGSA for search performance. It improves the search procedure and ensures that the performance is carried out systematically. The proposed algorithm was verified on six benchmark functions, including unimodal landscape functions and multimodal landscape functions by comparing the search performance for conventional algorithms. The study found that the NGCFGSAM outperformed the conventional algorithms. The experiment also analyzed the results with statistical techniques. It could affirm that the proposed algorithm enhances the performance of search performance. Moreover, the study found that the proposed algorithm has the global optimum approach more than the conventional algorithms. However, the experiment of premature convergence rate is not tested yet in this paper. For future works, researchers would investigate and rigorously prove the parameter turning for convergence rate. More benchmark functions and more algorithm comparison tests are required.

7 Availability of Data and Material

Data can be made available by contacting the corresponding author.

8 References

Dahiya, B. P., Rani, S., & Singh, P. (2019). A hybrid artificial grasshopper optimization (HAGOA) meta-heuristic approach: A hybrid optimizer for discover the global optimum in given search space. *International Journal of Mathematical, Engineering and Management Sciences*, *4*(2), 471-488.

Das, P. K., Behera, H. S., & Panigrahi, B. K. (2016). A hybridization of an improved particle swarm optimization and gravitational search algorithm for multi-robot path planning. *Swarm and Evolutionary Computation*, *28*, 14-28.

Dowlatshahi, M. B., & Nezamabadi-pour, H. (2014). GGSA: A grouping gravitational search algorithm for data clustering. *Engineering Applications of Artificial Intelligence*, *35*, 114-121.

Fox, B. R., & McMahon, M. B. (1991). Genetic operators for sequencing problems. *In Foundations of genetic algorithms*, *1*, 284-300.

Guo, Z., Zhang, W., & Wang, S. (2021). Improved gravitational search algorithm based on chaotic local search. *International Journal of Bio-Inspired Computation*, *17(3)*, 154-164.

Hosseinabadi, A. A. R., Kardgar, M., Shojafar, M., Shanshirband, S., & Abraham, A. (2016). Gravitational search algorithm to solve open vehicle routing problem. *In innovations in Bio-Inspired Computing and Applications*, *Springer*, *Cham*, *424*, 93-103.

Jebari, K., & Madiafi, M. (2013). Selection methods for genetic algorithms. *International Journal of Emerging Sciences*, *3*(4), 333-344.

Katoch, S., Chauhan, S. S., & Kumar, V. (2021). A review on genetic algorithm: past, present, and future. *Multimedia Tools and Applications*, *80*(5), 8091-8126.

Kim, T. K. (2017). Understanding one-way ANOVA using conceptual figures. *Korean Journal of Anesthesiology*, *70*(1), 22.

Kumar, Y., & Sahoo, G. (2014). A review on gravitational search algorithm and its applications to data clustering & classification. *International Journal of Intelligent Systems and Applications*, *6*(6), 79-93.

Mansouri, R., Nasseri F., & Khorrami, M. (1999). Effective time variation of G in a model universe with variable space dimension. *Physics Letters A*, *259*(3-4), 194-200.

Michalewicz, Z. (1992). *Genetic Algorithms+ Data Structure= Evolution Programs Springer*, New York.

Michalewicz, Z., & Schoenauer, M. (1996). Evolutionary algorithms for constrained parameter optimization problems. *Evolutionary computation*, *4*(1), 1-32.

Packiasudha, M., Suja, S., & Jerome, J. (2017). A new cumulative gravitational search algorithm for optimal placement of FACT device to minimize system loss in the deregulated electrical power environment. *International Journal of Electrical Power & Energy Systems*, *84*, 34-46.

Premalatha, K., & Natarajan, A. M. (2009). Hybrid PSO and GA for global maximization. *International Journal of Open Problems Compt. Math*, *2*(4), 597-608.

Rashedi, E., Nezamabadi-Pour, H., Saryazdi, S., & Farsangi, M. M. (2007). Allocation of static var compensator using gravitational search algorithm, *World*. *1*, *10*.

Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2009). GSA: a gravitational search algorithm. *Information sciences*, *179*(13), 2232-2248.

Santra, D., Mukherjee, A., Sarker, K., & Mondal, S. (2021). Hybrid Genetic Algorithm-Gravitational Search Algorithm to Optimize Multi-Scale Load Dispatch. *International Journal of Applied Metaheuristic Computing*, *12*(3), 28-53.

Saravanan, C. & Srinivasan, K. (2016). Optimal extraction of photovoltaic model parameters using gravitational search algorithm approach. *Circuits and Systems*, *7*(11), 3849-3861.

Pattrawet Tharawetcharak is a Ph.D. student at the Graduate Program in Engineering Management, College of Innovative Technology and Engineering, Dhurakij Pundit University, Bangkok, Thailand. He got a B.Eng. (Advanced Materials and Nanotechnology), and an M.Eng (Engineering Management) from Silpakorn University, Nakhon Pathom, Thailand. His researches are Information Systems and Computer for Engineering Management.

Tekn. Dr. Aumnad Phdungsilp is an Assistant Professor of Energy Management at Graduate Program in Engineering Management, Dhurakij Pundit University, Bangkok, Thailand. He holds an MSc. (Sustainable Energy Engineering), Tekn. Lic. (Energy Technology), and Tekn. Dr. (Civil and Architectural Engineering) from KTH Royal Institute of Technology, Sweden. He also received a Ph.D. in Industrial Engineering from King Mongkut’s University of Technology North Bangkok, Thailand. His research focuses on Multi-objective Optimization of Energy Systems and Building Services.

Dr. Suparatchai Vorarat is an Assistant Professor of Engineering Management at the Graduate Program in Engineering Management, Dhurakij Pundit University, Bangkok, Thailand. He got a bachelor’s and a master’s degree in Production Engineering from King Mongkut's Institute of Technology North Bangkok, Thailand. He received a Ph.D. in Engineering Management from The Robert Gordon University, Aberdeen, Scotland, United Kingdom. His research focuses on Life Cycle Costing and Maintenance Management.