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APPLICATION OF ADAPTIVE ELITISM OPERATOR IN FIREFLY ALGORITHM FOR OPTIMIZATION OF LOCAL AND GLOBAL SEARCH

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ABSTRACT

There are two important components in a meta-heuristic algorithm, namely, Diversification and Intensification. These components can be fine-tuned for the optimized execution of a meta-heuristic search algorithm. The firefly algorithm (FA) is the latest in a series of meta-heuristic algorithms. Although the FA has proven to be efficient in local searches, there are times when it might get trapped in several local optima, as a result of which it is unable to efficiently conduct a complete search. In the pursuit of global space scaling, this algorithm needs to generate different solutions leveraging on diversification. The function of updating the effectiveness of diversification in a search algorithm can be performed by elitism operators. In this study, a strategy was proposed to upgrade the FA concerning static issues. The methodology involved the hybridization of elitism with the standard firefly algorithm, and this modified version was known as the AFA. Also, another distribution was introduced to revamp the entire search process in the FA using a t-way test generation (t referring to the strength of the interaction). The experimental results demonstrated that the Elitism firefly algorithm (eFA) had better performance than the standard FA and also than the other up to date algorithms in terms of robustness and the convergence speed.

Keywords: *Firefly Algorithm, Elitism, T-way testing, Intensification, And Diversification.*

1. INTRODUCTION

A new elitism based firefly algorithm (eFA) for local and global optimization is presented in this paper. The algorithm proposed involves of T-way testing and elitism as the core features and intend at enhancing the exploration and exploitation characteristics of firefly algorithm.

Global optimization, which is used in various engineering applications, such as remote sensor networks, picture handling, and antenna plans, has grown in the past decades. Also, issues relating to global optimization, such as its non-linear nature and multiple local optima, are daunting tasks that need to be resolved [1],[2]. To tackle such optimization issues, researchers continually proffer innovative optimization algorithms. Nonetheless, it is evident that these optimization algorithms have their challenges too. Many researchers and specialists, therefore, have continually proposed novel approaches or algorithms as improvements over existing methods as the solutions delivered by previous algorithms have yet to reach the upper bounds in problem instances [3]. These evolving optimization algorithms have been classified in various ways in existing studies. In a straightforward approach, algorithms can be classified into two categories depending on their nature, namely, deterministic and stochastic algorithms, and algorithmic methods are naturally classified as deterministic and stochastic algorithmic methods. Deterministic algorithms involve a thoroughly methodical approach, where the paths, as well as values of all the variables and functions found in their designs, are repeatable[4]. Stochastic algorithms come in two forms, i.e. meta-heuristic and heuristic. Naturally-motivated meta-heuristic algorithmic methods include the genetic algorithm, particle swarm optimization, ant colony optimization, cuckoo search, artificial bee colony, and the firefly algorithm (FA). These are some of the meta-heuristic algorithms that are fast becoming incredibly and progressively efficient in taking care of current global optimization challenges[5],[6]. Meta-heuristic algorithms have advanced over the last three decades, and most of them have been generated through observing how nature tackles complex optimization issues that are dependent on organic procedures in nature[1],[7]. Two primary components in meta-heuristic algorithms are used for optimizing their performance, namely, the intensification and diversification components, which are also known as exploitation and exploration, respectively [8].

Through their intensification component, algorithms investigate districts in anticipation of discovering better solutions, whereas, through diversification, every area in the hunt space is assuredly reached. Consequently, the performance of meta-heuristic algorithmic methods is reliant on both the diversification and intensification operations [9]. In investigating search spaces on a global scale, meta-heuristic algorithms must produce scopes of solutions using diversification strategies. Among the latest meta-heuristic algorithmic methods is the FA, which mimics the behaviour of the firefly in nature. The firefly algorithm is extremely efficient with local searches, but may at times become trapped in numerous local optima, and hence, it may not be acceptable for global searches [7],[10]. Furthermore, the parameters of the firefly algorithm cannot be changed during iterative operations.

In the current research, various operations for diversification and intensification[11] were derived from current algorithmic methods. Among these were the mutation, hybrid, and selection operations of the genetic algorithm (GA)[12], the attractiveness operation of the firefly algorithm (FA), the Tabu operation of the Tabu search (TS)[13] , the random stroll or levy flight operation of the flower pollination algorithm (FPA)[14], and the levy flight and elitism operations of the cuckoo search (CS). Elitism involves the duplication of a small set of the fittest candidate solutions, which remain unmodified until the next generation. This may, at times, radically impact the execution as it ensures that the elitist algorithm (EA) wastes no time on re-finding newly discarded partial solutions. Candidates that are unmodified and protected via elitism remain qualified for parent selection in terms of raising the remainder of the succeeding generation.

In this paper, at-way strategy dependent on elitism in the firefly algorithm known as the (eFA) was proposed for generating a test case and to enhance the performance of the firefly algorithm in static issues. The methodology included the hybridization of elitism with the standard firefly algorithm. Therefore, another distribution was introduced to enhance global as well as local searching in the firefly algorithm. The paper is structured as follows: Section 2 presents an outline regarding the t-way test; Section 3 analyzes the pertinent literature; Section 4 outlines in detail the recommended strategies; Section 5 shows the experimental outcomes; and the final section summarises the conclusions.

A. T-way Testing Summary

Every software constitutes several combinations of input options (an example is shown in Figure 1) that must be examined prior to its introduction into the market. However, considering the constraints of time, resources, and a large number of combinations, it will be extremely difficult to test all the various possible combinations. Hence, there arises the issue of combinatorial testing, which is a strategy that involves sampling to discover a subset of test cases that will be able to test the entire system. The concept of combinatorial (t-way) testing focuses mainly on tests of various combinations of dissimilar values. This process is naturally based on the observation that many faults can be triggered by sequences of interacting input parameters, rather than the practice of testing all combinations via an exhaustive strategy [15]. Test values are produced for input parameters that were selected with the goal of generating combinations of dissimilar values for all the t-parameters that occur one or more times, wherein t denotes the strength of the interaction [16],[17]. However, a number of meaningful meta-heuristic algorithmic methods have been developed independently of t-way strategies. Basically, t-way test is comprised of a sampling approach that is utilized to reduce or eliminate the number of tests systematically in accordance with the interaction coverage strength (termed as t). In particular, the at-way test involves at least one t-way combination that must be covered. From the 'proofing tab' in the 'options dialogue' found in MS Excel (Figure 1), six feasible configurations are available for testing, where each configuration features dual values (unchecked or checked). To begin with, the 'French mode'' provides three possible values, the 'Spanish mode'' provides three feasible values, and the 'Dictionary language' features 54 attainable outcomes. For thorough testing of the proofing tab, the number of data on which testing is to be performed would be 26 x 54 x 3, which is equal to 10,368. On the assumption that each testing of data is executed in 5 minutes, some 28 days would be needed for the finish the exhaustive testing of the 'proofing tab' [18].

Probable combinations in such a system would entail 2^{30}= 1,073741,824 test data and thus, exhaust 10,214 years, considering the 7 minutes spent on

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every test data. These days, research on combinatorial testing is aimed at generating the least attainable test data. An answer for this problem entails non-deterministic polynomial-time hard (NP-hard) methods (i.e. Non- deterministic Polynomial-time) problem [19],[20].Thus far, numerous approaches have been introduced with various tools for determining the minimum possible test suite in polynomial time.

The motivation to this study to present new strategies. Hence, the paper suggested a t-way test suite generation strategy based on elitist firefly algorithm, (TTSGEF). The strategy is developed to cater all three types of support interactions; uniform strength, variable strength and IOR. Software testers are flexible in selecting the support interaction to be used [21]. The strategy employs metaheuristic algorithm and Firefly Optimization to support in producing a near-optimal test suite size.

B. **Elitism**

In the most traditional way for evolutionary algorithms, elitism suggests that the best solution found is utilized to work for the next generation. Elitism involves the replication of a small set of the fittest candidate solutions, which remain unaltered, into succeeding generations. The condition can at times radically impact execution by ensuring that the EA wastes no time on re-finding newly-disposed partial solutions. Candidates who stay protected and unmodified via elitism all meet the requirements for parent selection in terms of rearing the remainder of the succeeding generation. Elitism operators are used in various algorithmic methods to ensure a solution of high quality will proceed to the succeeding generation [22]. Elitism ensures only a highly-fit firefly population passes to the next generation.

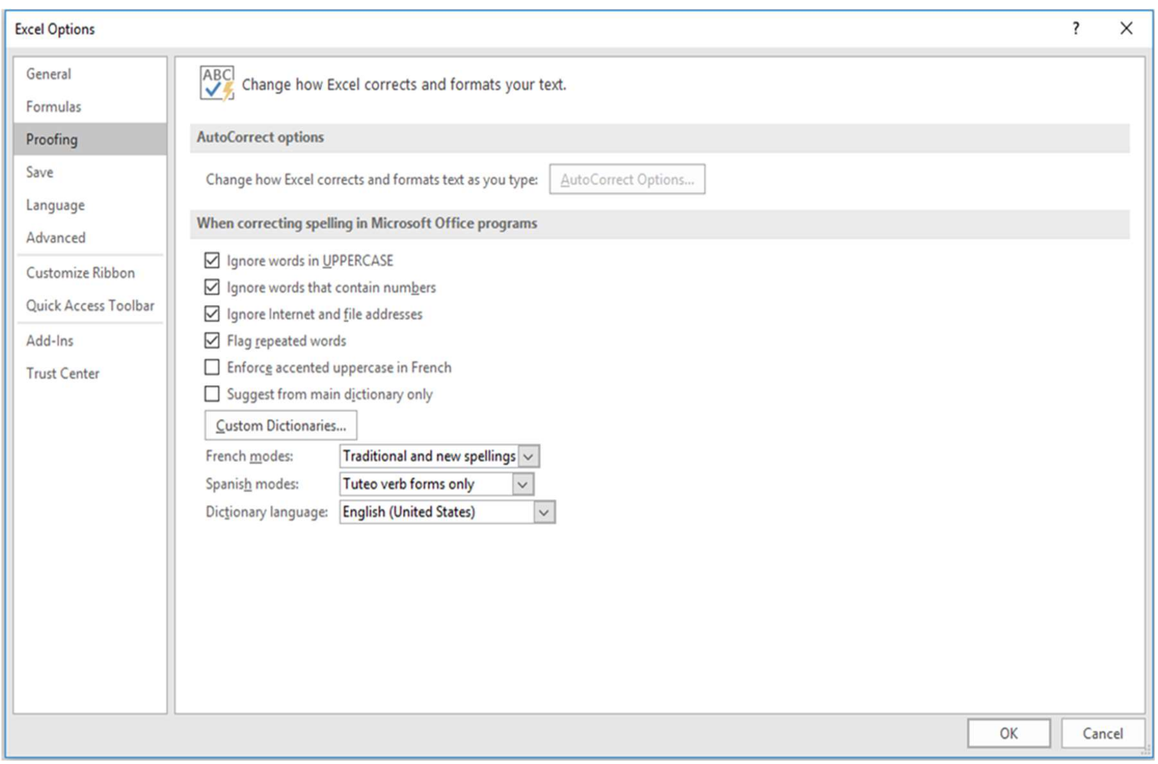

Figure 1: Proofing Option on Microsoft Excel.

2. RELATED WORK

The t-way test has been ordered by many existing studies in different categories. According to [23], there are eight groups of t-way tests that are dependent on the focal point to the article. These groups incorporate system modelling under the test and the generation of test cases, where meta-heuristic approaches are mostly utilized to generate articles [24]. The constraints include fault diagnosis and characterization failure, improvements in the testing methodology, and the application of CT(App), test cases for prioritization (Prior) and lastly, the metric evaluation. In a more in-depth or extended methodology, the t-way test approach is divided into three main territories. More specifically, the strategy approach is further separated into two, namely, the one-parameter-at-a-time strategy (OPAT) and the one-test-at-a-time strategy (OTAT). The search technique is isolated into two main types, namely, the meta-heuristic and computational search techniques. These techniques support interactions that can be separated into variable strengths that are, sub-separated into uniform strength and the input-output based relation (IOR) [25],[26],[27]. Moreover, recently [28] categorized the methods for the assembly of chips for t-route testing into two main groups, namely, computational methodologies and mathematical methodologies. Mathematical methodologies use lightweight mathematical functions for the development of test cases without enumerating any of the combinations. The types of strategies that adopt these methodologies include the Combinatorial Test Services (CTS) strategy and the T-Config strategy, which is restricted to low configurations of about $t \leq 3$. Meanwhile, computational methodologies are like the approach strategy in [25]. These are grouped into two approaches, namely, the OTAT and OPAT approach. In the OPAT-based approach, a complete test suite is developed for the lowest interaction parameters, and for every iteration, one parameter is added until all the parameter combinations are well-secured. However, the OTAT approach includes the development of one test case for every iteration, which covers a higher number of revealed interactions among the elements. This is repeated until all the interactions of the elements are well-secured. The strategy starts with a randomised solution set, which then undergoes a procedural progression towards determining the best test cases using fitness functions. This process iterates until every combined parameter input is fully secured. Meta-heuristic search strategies have been shown to generate optimal testing suite estimates in contrast to those obtained through computational search strategies [25],[28],[29] stated that both the OTAT and meta-heuristic search techniques comprise the most capable zones of analysis regarding t-way combinatorial tests. Also, it was emphasised that the acceptance of meta-heuristic algorithmic methods relies on t-way testing suite generation. In this work, several meta-heuristic approaches were effectively associated with the t-way testing; for instance, the cuckoo search (CS), particle swarm optimization (PSO), simulated annealing (SA). Algorithm [30], flower pollination algorithm (FPA), ant colony algorithm (ACA), Tabu search (TS), genetic algorithm (GA), sine cosine algorithm (SCA), and firefly algorithm (FA). Numerous researchers have applied the 2-way test to these algorithms in order to optimize their performance. [31] implemented the GA, SA, and TS algorithms in 2-way tests. The SA is an isolated physical algorithmic method that is derived from physical tempering procedures. The GA was further utilized as an earlier method for implementing population-based algorithms in t-way test cases. The algorithm begins by finding the optimum test case through several positions, and then, it repeatedly applies hybrid, mutation and selection operations that mimic the process of natural selection in biological macroevolution. Later, researchers such as [32] extended the SA for supporting tests of 3-way interactions. [33] also extended the ACO and GA to support tests of 3-way interactions. The experimental results by [34], who analyzed the performances of the GA, SA, and TS, showed that the performance of SA is better compared to the GA and TS. [35] employed the PSO algorithm in a 2-way test, and [19] used it similarly in t-way tests. The algorithm relies upon the behaviour of swarms of feathered creatures as well as fish in their search for sustenance. More recently, Alsewari et al. [36], implemented a further t-way approach known as the harmony search (HS) strategy that covers artistic behaviours in the creation of further tones. Nasser et al. [22] developed the firefly pollination-based approach (FPA) for use in at-way test generation. Also, the method is utilized to generate sequences of t-way test suites that mimic the pollination behaviour of flowering plants. The FPA was observed to be executed in two dissimilar stages, namely; local and global pollination. These are regulated by the probability parameter. Local pollination transports the particles within comparable blooms that have females present for pollination, whereas global pollination exploits a levy flight for transporting dust particles between flowers. Alsariera implemented the bat algorithm (BA) int-way tests as an approach that is comparable to the FA [37].

Nevertheless, the BA follows the hunting behaviour of microbats that can locate their prey in total darkness.

Sabharwal and M. Aggarwal [15] followed the premise that the recognition of optimal incentives int-path system testing will continue as an open issue. They introduced a means of identifying and dealing with interactions that occur within source codes, thereby reducing the number of interactions for testing. DD path charts were produced from the source codes, and the interacting elements were identified using DataStream methods. Dual contextual analyses were also considered to demonstrate the proposed methodology. The experimental findings showed that the proposed approach significantly reduced the number of

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interactions for testing without any meaningful reduction in the ability to detect faults. The approach can be extended to substantial and measurable structured projects. A further strategy in the t-way test generation was developed in the research by [38], where a hyper-heuristic-based approach was introduced using 5 meta-heuristic algorithms, namely particle swarm optimization, Tabu hunt, global neighborhood, teaching-learning-based optimization, and CS (cuckoo search). Based on prior methodologies, [17] developed a new approach known as the adaptive teaching-learning-based optimization (ALTBO). This strategy enhances the conventional TLBO performance, hence resulting in a decent balance between the diversification and intensification processes via the implementation of fluffy derivation rules. Farahani [7] recommended a half-and-half model to improve firefly algorithm (FA) by using learning automata to adapt the behaviour of the firefly and the utilization of a genetic algorithm to upgrade global hunt methods and generate newer solution sets. Since the parameters of the FA do not change between iterations, the study presented a means for stabilizing the movements of the firefly between iterations. These experimental results showed that in terms of its exactness and execution, the cross-breed variant was superior to the initial firefly algorithm.

Similarly,[39] introduced an adaptive firefly algorithm (FA) termed the (AFA). The strategy used here involved selections of the parameter, α from among a group of candidate solutions (α1, α2, . . ., α10). The αk selection was established via the probability (prob k), wherein k = 1, 2, 3,…, 10. The learning period (LP) technique is used to update the dependence of the prob k on improvements to the fitness of the firefly. Even though the AFA achieved promising solution sets, its implementation was remarkable. In an equivalent strategy, [40],[41] adapted the firefly algorithm to obtain a variant known as the (AFA). Three powerful approaches were combined in the AFA: the distance-based coefficient of light absorption; dim coefficient upgrading of fireflies for efficiently sharing distinctions in information derived from interesting subjects; and five different unique methods for the randomization parameters. The promising parameter selections for these methods were examined to ensure the efficient execution of the AFA. More recently, [1] proposed a half-and-half population-based global optimization algorithm called the hybrid firefly algorithm (HFA) by joining the merits of the firefly algorithm (FA) and differential evolution (DE). The FA and DE are executed in parallel to allow the dissemination of information within the population, thereby upgrading towards productivity. It was observed from the results of experiments on the HFA in contrast to standard variants of the FA that the DE was better. The newly-proposed algorithm was likewise better than the particle swarm optimization (PSO) in its ability to keep away from the local minima and to increase the rate of assembly [42]. The optimized execution of existing algorithms has continued to advance in the literature, as evidenced by the several half-and-half types of the first or standard algorithm. For example, produced two mixed algorithms known as the mutation-FPA (mFPA) and elitism-FPA (Efpa) utilizing both mutation and elitism operators in the flower pollination algorithm. These variants outperformed the standard FPA [22], [43]. A review of the literature where variants of the firefly algorithm in exist revealed that all the studies connected different combinations of at least two standard algorithms to deliver variants or hybrids of the standard FA. It was observed that the execution of these hybrids was better than that of the standard FA algorithm.

3. PROPOSED ALGORITHM

This section describes the proposed strategy, known as the AFA. The standard issues concerning the FA are, for instance, the premature association and trapping of the FA in local districts when utilized to oversee complex issues with different local optima. This study contributes to the literature by developing a variant of the FA using both an elitism operator and at-way testing strategy. The elitism is useful towards increasing the diversity of the fireflies and ensure that only the best solution with high quality can pass to the next generation [44][45]. The AFA overcomes these shortcomings in the FA and optimizes the local and global search, this variant is elucidated in the upcoming sections. The AFA is a unified strategy based on the FA for t-way test generation and elitism. Standard FA starts by initializing the attractiveness of the firefly (using light intensity). Then, the FA generates the ratio of the good population to the overall population. Finally, the algorithm updates each solution by performing a local or global search. The proposed study included the hybridization of the elitism operator in the FA to redesign the optimization of the global and local hunts. The new algorithm, AFA, searched after two essential steps. The initial phase included generating interaction element lists for the attendant criteria, namely, the number of parameters, parametric values, and interaction strength, t. These generated lists contained all possible combinations for input parameters utilizing the t-way test.

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Appropriate parameter selections wholly determined the quality of the solutions and the effectiveness of the query. The next phase involved discovering an optimal test case using FA and elitism.

This study considered the proposed strategy for AFA, which combined the attractiveness of FA with the capacity of elitism to replicate a small part of this set of fittest subjects unaltered through the next iteration to enhance the associated speed along with the population diversity. Elitism can provide a decent blending capability within this population and high diversity within this population. Elitism may similarly finish local searches in the middle of an operation. Given these descriptions, the basic AFA steps were condensed into a pseudo-code introduced in Figure2, where the insert presents a flowchart for the FA and elitism.

Each firefly will represent one test case we generate random of test cases or random fireflies, and then all fireflies will be measure on the number of computation:

Stage 1

Step1: Generate the population of firefly: A random list of some test cases is generated, called the fireflies

Step2: calculate the attractiveness and distance for each firefly: if a test case covered one combination pair from every combination list, it was believed to include a maximum coverage (i.e., weightage). Thereafter, it is added to the final test suite. On the other hand, if it did not include the maximum coverage, it is added to the memory of the fireflies, wherein their memory (population) is filled with the candidate fireflies

Stage 2

Step 1: move firefly to brighter one: These test cases undergo an improvisation process, for deriving a better value of the intensity, which indicates the test case weightage. It was seen that if these improvised selected test cases showed a better weightage value, the primary test case is replaced by the improvised test case.

- **To improvisation-based dynamic elitism**

The elitism is applied as follows, for fixed Iteration a new firefly will be generated based on the global stage or local stage depends on the calculated success rate (measurement) to obtain the best values for every test cases.

Stage 2: has two branches based on success rate, if the success rate is lower than Rand:

- **Branch 1: Global operator based on the equation:**

$x_i = x_i + \beta_0 e^{-yr^2}(x_j - x_i) + \alpha \mathcal{E}_i$; Update each value of the new test case and then check the new weight, after that update the test list.

- **Branch 2: local operator**

local search will update only some values based on the condition [0.1-1], if success, only the parameters or values will update based on this property [0.5] “not all the value property. “If the new weight of the test case is better than the current weight it will replace the new with the current”

To enhance the local and universal population the proposed algorithm caries out the operation of elitism by using the steps as; if the success rate is greater than the random it will get global operator and check for the length of FA by iteration for the new Wight (gbest). It will put for the best test cases inside the memory else it will get local operator. If the random less than or equal to the probability [0,1] to dfine number of elite fly, then it will do iteration for maximum to check the new weight. As it gets the best weight for (test cases) added the memory for the final test suit until stop the iteration. In the proposed self-adaptive Firefly with elitism test list generation strategy, the poor solutions will be replaced by the new solutions based on local operator or global operator dynamically.

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FIGURE 2. Flow chart of AFA.

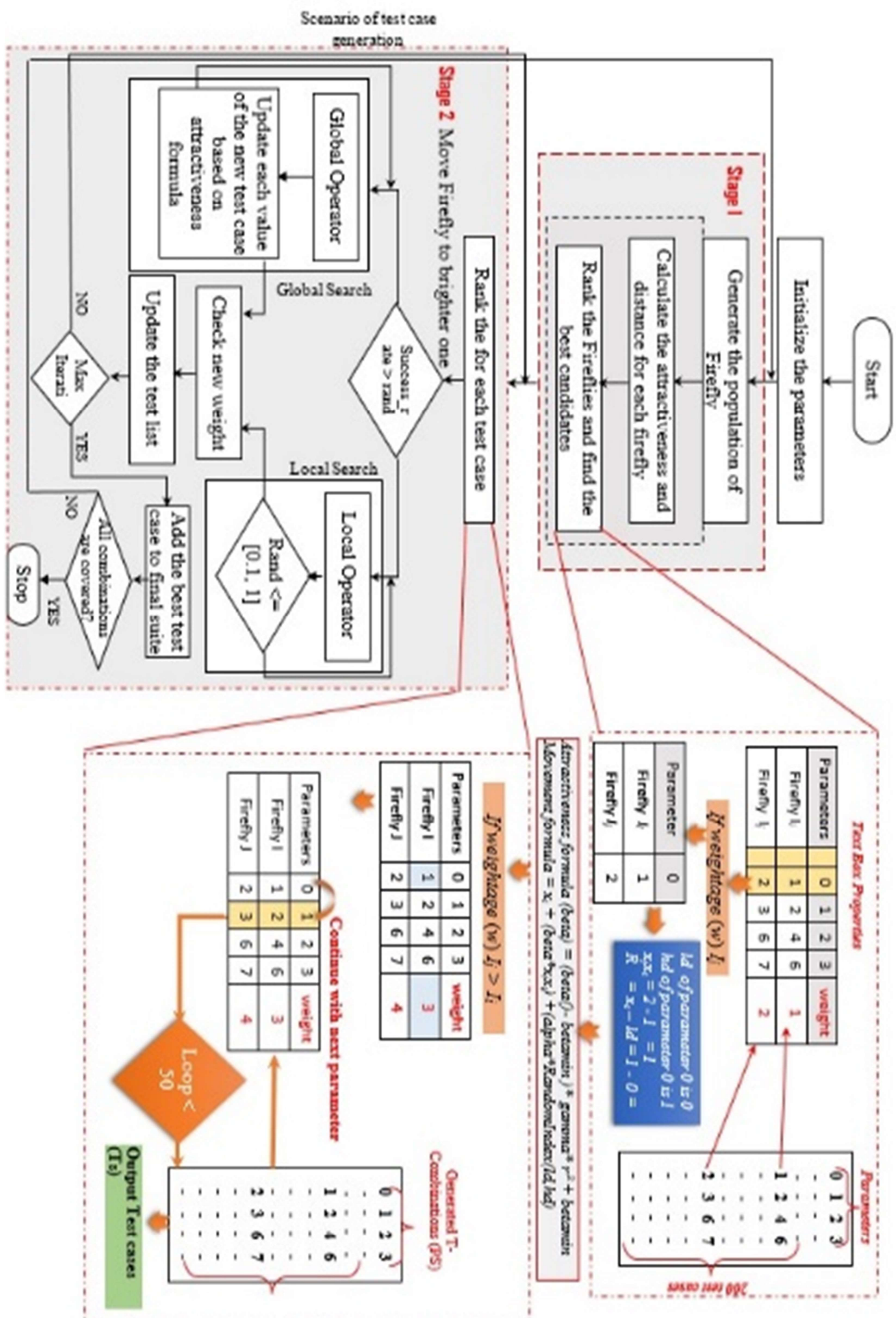

Table 1. Algorithm parameters for strategies of interestsn.

Algorithm	Parameters	Values
GA	Iteration	1000
	Population size	25
	Best cloned	1
	Random crossover	0.75
	Tournament selection	0.8
	Max stale period	3
	Gene mutation	0.03
	Escape mutation	0.25
ACA	Iteration	1000
	Number of ants	20
	Pheromone control	1.6
	Pheromone persistence	0.5
	Heuristic control	0.2
	Pheromone amount	0.01
	Initial pheromone	0.4
	Max stale period	5
	Elite ants	2
SA	Iteration	1000
	Cooling schedule	0.9998
	Starting term persistence	20
PSO	Iteration	100
	Population size	80
	Itertia weight	0.3
	Acceleration coefficients	1.375
CS	Iteration	100
	Population size	100
	Probability *ep*	0.25
HS	Improvisation	1000
	Harmony memory consideration rate	100
	Harmony memory consideration rate	0.7
	Pitch adjustment rate	0.2

Figure 3 presents the flowchart for AFA, which is the new algorithm. The AFA combines the optimization capabilities of the conventional FA with elitism operations. The conventional FA is base on the fact that fireflies are unisex and can be attracted by anyone of it. Similarly, the light intensity and the particular distance is always inverse with each other, implying that the air absorbed light will decrease as the distance between fireflies increases. Furthermore, the light intensity of fireflies is determined by the objective function to be optimized[46]. These allowed them to be combined to formulate a new solution. FA is controlled by three parameters: the randomization parameter α, the attractiveness β, and the absorption coefficient γ [47]. These parameters are adjusted to carry out the execution of the optimal solution to the optimization problem and the calculation of the firefly numbers[48]. This feature of the firefly is further enhanced by the elitism operator.

The elitism operator attempts to improve the populations quality by ensuring that only the brighter (elite) fireflies are passed for the next generation, and it also increases the population diversity. Therefore, enhancing the ability of the AFA algorithm in local and global search, as it can update each firefly by performing a local search or global search and evaluated its objective function. For a higher-quality solution, all approaches mentioned in Sections 1.1 and 1.2 were linked (t-way test generation and elitism). The FA does not retain memory; hence, no information can be extracted dynamically during searches. The AFA relies on memory that holds certain information drawn from previous searches, namely, certain histories for searches stored within the memory may be used to generate candidate lists of solutions and select a newer solution. This condition enhances the dynamic probability or property of FA.

4. EXPERIMENTAL RESULTS

This part describes the outcomes of the elitism operator in the FA The new AFA algorithm was compared with the standard FA. This comparison was carried out in two systems. First, the initial convergence rates of both the proposed and traditional algorithms were compared as system 1, and then, the new algorithm was also compared to existing algorithms as system 2.

A. Convergence Rate Analysis

The convergence rates of various algorithms were compared for the purpose of analyzing the performance of existing algorithms against the proposed algorithm (AFA). By considering the examples of individual problems in identifying a finite set of solutions, the convergence rate can simply be defined as the speed at which the production of meta-heuristic algorithms can achieve an individual finite set. Two strategies were applied to the two system configurations, as presented in Table 1. The employed measures were based on the AFA and FA. The first system had six parameters, with each parameter in system 1 having three values. The second system had nine parameters, with each parameter in system 2 having three values. In this study, the implementation and execution of the

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strategies were accomplished using NetBeans 8.0.1 with different iteration values (i.e. 100, 200, 300, 400, 500, 600 and 1000) Then AFA is executed twenty times for each iteration values, and the averages (Equation 1) of the best-obtained results are recorded.

$$\boldsymbol{Avrage} = \frac{1}{n}\sum_{1}^{n} x_i \quad (1)$$

Where i= 1,2,3….,n, and n is number of runs . x_i is the obtained test suite.

Figures 3 and 4 show the comparison of the convergence rates between the AFA and FA. The figures show the AFA performed better than the FA. Consequently, the introduction of elitism operators into the standard FA in the two cases led to an improvement in the quality of the solutions.

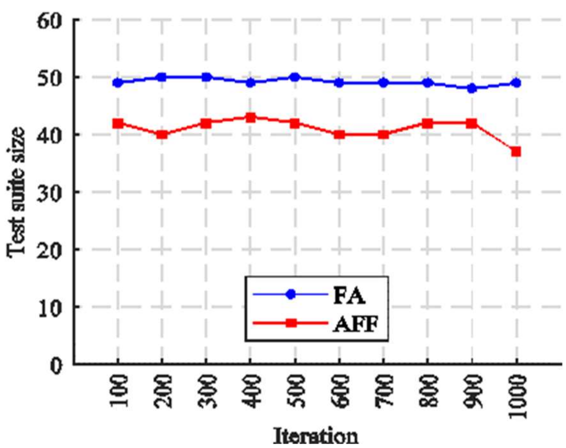

FIGURE 3. Convergence rates of FA and AFA for system #1

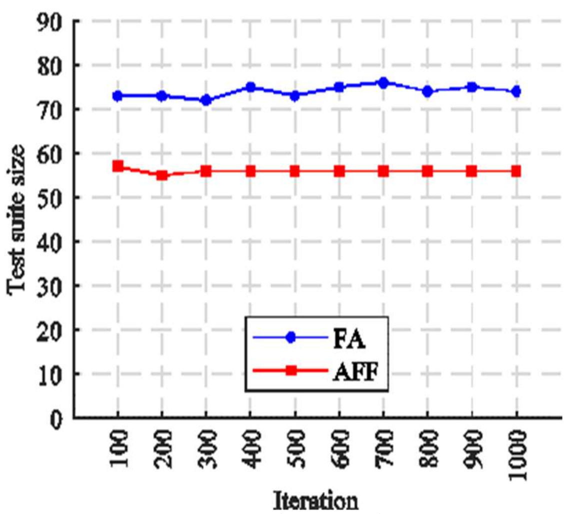

FIGURE 4. Convergence rate of FA, AFA for system #2

B. Performance Evaluation

This section shows a comparison of the new algorithm with the standard FA. The comparison also included current strategies or algorithms. The results of the suggested algorithm (AFA) were compared with the results of other studies, as [49],[36],[19],[50]. Up to this point, many system configurations were approved, as shown in Table 1. The cells set apart are labelled as NR to show “No Available Results.” The cells in intense font represent the optimal estimate completed by the strategy comperd to other existing strategies. By simply comparing FA and AFA; the cell is set apart with a dull cell to give the ideal esteem accomplished by the suggested strategy (AFA). The system column in the table points to the system configuration, where yx means that the system has x parameters, and y values for each parameter. Most of the strategies, including GA, SA, and ACO, sustained only t ≤ 3 as shown in Table 1 . Few strategies, for example PSO, HS, CS, FPA and its variants (eFPA and mFPA), and the newly proposed strategy, AFA sustained high interaction strength (t > 3). The results in Table 1 prove that in 10 out of 13 system configurations; the AFA performed better than the FPA and its variants eFPA and mFPA and achieved results comparable to the best test case estimate obtained by the other current strategies. Although at times, the performance of the AFA was below those of existing algorithms (PSO, HSS, and CS, which had values of 1209, 1186, and 1200, respectively), the results of the AFA were still within sensible values in those cases because of the enhancement of its population diversity through elitism.

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TABLE 2. COMPARISON OF FA WITH EXISTING ALGORITHMS

	General Computational-based Strategies						Meta-heuristic-based strategies												
Systems	Interaction	mAETG	AETG	IPOG	Jenn	AVG	SA	ACA	GA	PSO	HSS	CS	FPA	eFPA	mFPA[22][	FA		AFA	
																Best .N	Avg. N	Best .N	Avg. N
3^4	2	9	9	9	10	9	9	9	9	9	9	9	9	9	9	9*	10.56	9*	10.6
3^{13}	2	17	15	20	20	17	16	17	17	17	18	20	18	18	18	18	18.46	18*	18.8
5^{10}	2	NR	NR	50	45	NR	NR	NR	NR	45	43	NR	44	43	43	60	59.56	43*	43.2
8^{10}	2	NR	NR	117	104	NR	NR	NR	NR	109	105	NR	105	103*	104	164	162.73	107	105.36
15^{10}	2	NR	NR	373	336	NR	NR	NR	33	NR	342	NR	364	356*	358	593	579.96	382	372.1
3^6	3	NR	47	53	51	33	NR	33	NR	42	39	43	44	43	43	47	49.8	35*	43.3
2^{10}	3	NR	NR	NR	NR	NR	NR	NR	NR	17	16	16	16	16	16	19	19.5	16*	16.6
5^7	4	NR	NR	NR	NR	NR	NR	NR	NR	1209	1186	1200	1173	1162	1135	1475	1443.65	1159*	1128.1
5^8	4	NR	NR	NR	NR	NR	NR	NR	NR	1417	1358	1415	1338	1326	1335	1753	1710.6	1310*	1296.64
2^{10}	5	NR	NR	NR	NR	NR	NR	NR	NR	82	81	79	80	78	74	89	89.3	72*	80.86
3^7	5	NR	NR	NR	NR	NR	NR	NR	NR	441	NR	439	437	434	435	460	452.06	432*	424.1
2^{10}	5	NR	NR	NR	NR	NR	NR	NR	NR	158	158	157	156	155	158	178	176.5	155*	154.06
3^7	6	NR	NR	NR	NR	NR	NR	NR	NR	977	NR	973	962	952	954	995	974.86	943*	959.74

.

Show the smallest test suite size, (NR) No results available in the respective publication

Tables 2 show that AFA gets the smallest test suite in the most maximum case, the only AFA has two configurations managed to outperform AFA, where the test suite size produces by AFA is equal to 107 test cases during the test suite size. Produces by eFPA is 103 test cases, that is, in the case of p = 10. AFA appears to generate the most optimum results in most of the configurations as marked with (*) owing to the good balance between global stage and local stage through the obtain the best values for every test case.

5. STATISTICAL ANALYSIS FOR T-WAY RESULTS

The statistical analysis is performed using the Friedman([51], and Wilcoxon [52] signed-rank test with Bonferroni-holm correction ($\propto_{holm}$) at 95% confident level (i,e, $\propto = 0.005$). I n this section, the stsisical analysis is divided in two sub sections. The First sub sections consider the result of the t- way strength benchmarking while the second sub-section considers the results of the mixed-strength benchmarking. The strategies with N/A and N/S results are considered incomplete and ignore samples as there is no available result for the specified test configuration.

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Table 3 Wilcoxon signed-rank (post-hoc) tets for table 2

Categories	Pair comparison	Ranks			Asymp. Sig. (2-tailed)	Conclusion
		Negative Ranks	Positive Ranks	Total		
Meta-heuristic-based strategies	PSO - AFA	1	6	8	0.034	*Reject the mull hypothesis* H_0
	HSS - AFA	0	5	8	0.043	*Reject the mull hypothesis* H_0
	CS - AFA	0	6	8	0.027	*Reject the mull hypothesis* H_0
	FPA - AFA	0	5	8	0.043	*Reject the mull hypothesis* H_0
	eFPA - AFA	0	4	8	0.067	*Reject the mull hypothesis* H_0
	mFPA - AFA	1	4	8	0.345	*Reject the mull hypothesis* H_0

Note: the results for (mAETG, AETG, IPOG, Jen, AVG, SA, ACA and GA) are ignored.

Table 4 Friedman test for table 2

Friedman	Conclusion
Degree of freedom = 6, ∝= 0.05 Friedman statistic (p-vale) = 0.018 Chi-square vale (x^2) = 15.329	0.018<0.05 (i.e p-value <∝). Thus, reject H_0 and proceed to the post-hoc test.

(courtesy: IBM SPSS version 26)

From the results of the experiment, the Wilcoxon test statistic is calculated and converted into a conditional probability P-value. A small P-value means that it is strong evidence to reject the null hypothesis H_0 (i.e. there is no difference between two strategies' results) in favour of the alternative hypothesis. Decision making is based on ∝ or significance level.
The statistics for Friedman test and Post-hoc Wilcoxon signed-rank test is used between AFA and each strategy and it is presented in Tables 3-4 through 2 with confidence of 95% level (i.e. α =0.05). As the tables show the Post-hoc Wilcoxon Rank-Sum Tests give negative ranks (i.e. a number of cases that AFA unable to outperform another strategy), and positive ranks (i.e. number of cases that AFA is better than another strategy), along with ties. The column labelled Asymp. Sig. (2-tailed) shows p-value probability: if p-value less than 0.005, as recommended in [53], there is no significant difference between the compared results. For the statistical significance, all the AFA (Size) results are based on 20 executions. The average size (Average) are reported for AFA. The test is performed using an SPSS software tool.

6. CONCLUSION

This research developed a variant of the FA algorithms that focuses on improving the searchability of the standard FA. The study adopted the elitism operator, and t-way testing approaches into the standard FA. The aim was to present that the strategy was adequately competitive related to other strategies in terms of the generated test suite size. The results prove that in supporting uniform interaction, AFA can compete with existing strategies. The elitism operator ensures that only the best solution found is utilized to work for the next generation. Therefore, elitism involves the replication of a small set of the fittest candidate solutions, which remain unaltered, into succeeding generations. The condition ensures that the AFA wastes no time on re-finding newly-disposed partial solutions. They are hence optimizing both local and global search capacity of the FA. For evaluating the effects of presenting elitism operators

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to the FA, comparative evaluations of the FA and AFA approaches and other current hybrids meta-heuristic algorithmic methods were also conducted. The results showed that the AFA strategy is an improvement over its standard algorithm (FA) and other existing algorithms owing to the enhancement of its population diversity by the elitism operators. With this promising performance of the AFA, it is further proposed that other constraints of the firefly algorithm, such as weak explorations in high-dimensional problems, be improved.

Generating the most optimal variable t way suite is an NP-hard problem; therefore, this field is still an active domain for research. This paper implemented AFA into an optimization problem related to the t-way test generation problem. The main contribution of AFFA supporting variable strength, AFA can generate a test suite up to t= 6 and can produce a good result with suitable performance. As a scope of our future work, we are planning to enhance the AFA to support Input-Out relationships as well as constraints.

FUTURE WORK

Given that the application of AFA presented in this study is still a prototype, an obvious starting point for future work Will is to complete the implementation to support automated test execution and other t-way test generation types. In particular, several by-way features needed to be included (. e. input-output relations t-way, sequencing t- way and constraint t-way).

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