Review of Nature Inspired Metaheuristic Algorithm Selection for Combinatorial t-way Testing

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ABSTRACT Metaheuristic algorithm is a very important area of research that continuously improve in solving optimization problems. Nature-inspired is one of the classifications of metaheuristic algorithm that are becoming more popular among researchers for the last decades. Nature-inspired metaheuristic algorithms contributes significantly to tackling many standing complex problems (such as combinatorial t-way testing problem) and achieving optimal results. One challenge in this area is combinatorial explosion problem which always intended to find the most optimal final test suite that will cover all combinations of a given interaction strength. As such, test case generation is selected as the most active research area in combinatorial t-way testing as Non-deterministic Polynomial-time hardness (NP-hard). However, not all metaheuristics are effectively adopted in combinatorial t-way testing, some proved to be effective and thus have been popular tools selected for optimization whilst others are not adopted. This research paper outlines hundred and ten (110) outstanding nature-inspired metaheuristic algorithms for the last decades (2001 and 2021) such as Coronavirus Optimization Algorithm, Ebola Optimization Algorithm, Harmony Search, Tiki-Taka Algorithm, and so on. The purpose of this review is to revisit and carry out up-to-date review on these distinguished algorithms with their respective current state of use. This is to inspire future research in the field of combinatorial t-way testing for better optimization. Thus, we found that all metaheuristics has a simple structure to be adopted in different areas for becoming a more efficient in optimization. Finally, we suggested some future paths of investigation for researchers who are interested in the combinatorial t-way testing field to employ more of these algorithms by tuning their parameters setting to achieve an optimal solution.

INDEX TERMS Metaheuristic Algorithm, Nature Inspired, Combinatorial t-way testing, Test case Optimization.

I. INTRODUCTION
Over 30 years, optimization is growing in the aspect of research areas for the purpose of providing an optimal solution from complex problems by developing several computationally powerful algorithms. Optimization is the process that mathematically adjust the inputs of a device to find a minimum outputs. From many available solutions, we applied optimization techniques to find the best possible solution. Optimization problems have been started since 1940’s and it is deployed in different ways that consists of a function and a set of constraints. Optimization problems are very difficult to solve, despite many applications are dealing with Non-deterministic Polynomial-time hardness (NP-hard) problems [1], [2].

All optimization problems are classified into various categories like combinatorial optimization, linear programming, integer programming, and so on. In fact, some research has proven that all optimization challenges from the practical aspect and the theoretical aspect aimed at searching for the best from a set of variables [3]. They are divided into two categories: those that their solutions are programmed with real-valued variables, and those that their solutions are programmed with discrete variables. One of the most recent
challenges in optimization is combinatorial explosion problem, that deals with test case generation. As a result, test case generation is selected as the most active research area in combinatorial t-way testing. Metaheuristics optimization method is very effective, as such, many algorithms are developed to tackle the standing problems [3].

Metaheuristic algorithm depicts the higher level of heuristics which are intended to find the best solution for a wide range of optimization problems. In the most recent time, many metaheuristic algorithms are applied effectively for solving optimization problems. These algorithms are used to solve a complex problem by obtaining the best solution (optimal). The metaheuristic algorithms are chosen to solve optimization problems owing to its simplicity, easy to implement, local optima avoidance, and can be exploited in wide range of problems from different disciplines [1], [4].

In recent years, several nature-inspired metaheuristic algorithms have emerged and are attracted by many researchers due to nature as a source of inspiration. However, the literature indicates that metaheuristic algorithms are commonly used in different areas like combinatorial t-way testing, but under-appreciated term [5]. In fact, not all the metaheuristics are effective in combinatorial t-way testing, even though some proved to be very effective and thus have been adopted for optimization whilst others are not adopted.

The aim of this paper is to identify the recent metaheuristics mechanism underlying nature-inspired approach for the last two decades (2001 to 2021), to carry out those mostly adopted and not adopted in combinatorial t-way testing addressing combinatorial explosion problem. Also, it will add to our broader understanding of metaheuristic algorithms and propose some guidance for future research in the field of optimization. Finally, it is also hoped that this research will shine some light on future developments in nature-inspired metaheuristic algorithms.

The rest of this paper is organized as the following sections: the overview of metaheuristic algorithm is presented in Section 2, Section 3 depicts the combinatorial t-way optimization problem model, Section 4 classifies and review the nature inspired metaheuristic algorithms, Section 5 presents the result, Section 6 present the discussion, and finally, Section 7 offerings the conclusion of the work.

II. METAHEURISTIC ALGORITHM

Metaheuristic was first introduced in Glover in the year 1986 named as modern heuristics, but later changed to metaheuristic. The metaheuristic is derived from the two Greek words (“meta” and “heuristic”); the heuristic means “to find”, while the meta means “beyond, in an upper level”. Metaheuristics is an approximate method of optimization algorithm that combines more than one heuristic methods in a higher-level framework with the assurance of finding optimal solutions in a short amount of time [6]. The term metaheuristic also used to refer to a problem specific implementation of a heuristic optimization algorithm according to the guidelines expressed in such algorithm.

Thus, different metaheuristics algorithms are applied successfully for solving problems like combinatorial optimization problem. The main target of these metaheuristic algorithms is to solve a complex problem, such that an optimal solution is obtained in a small amount of time [6]. Due to its popularity on the later time, the Search based Software Engineering (a.k.a. SBSE) confirmed the application of metaheuristic algorithm for solving software engineering related problems. The promptest metaheuristic class of algorithms includes the Ant Colony Optimization (ACO), Evolutionary Computation (EC), Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search (TS) [6]. More so, metaheuristic normally deals with optimization problems by adopting metaheuristic algorithms whereas the optimization can be seen as a method of minimizing or maximizing a problem. The minimization of optimization problem can be written mathematically as:

\[ f_i(x), \ldots, f(x), \ldots, f(x), x = (x_1, \ldots, x_d) \]

\[ h_j(x) = 0, (j = 1, 2, \ldots, J) \]

\[ g_k(x) \leq 0, (k = 1, 2, \ldots, K) \]

Where \( f_1, f_2, f_3, \ldots, f_i \) are the objective functions, \( h_j \) is the equality constraints, and \( g_k \) is the inequality constraints. If \( i=1 \), then the function is known as single-objective optimization, whereas if \( i \geq 2 \), the function is known as multi-objective optimization. Overall, the above functions \( f_i, h_j \) and \( g_k \) are considers as nonlinear functions.

However, metaheuristic algorithms are classified into different viewpoint depending on the characteristics selected to differentiate among them. Literature review [7] reveals a way of classifying metaheuristics as follows: nature inspired vs. non-nature inspired, population-based vs. single point search, dynamic vs. static objective function, and memory usage vs. memory-less methods. Furthermore, many literatures consider that metaheuristic search methods can reach a better performance when an appropriate balance between exploration and exploitation of solutions is achieved [4], [8].

Exploration and Exploitation

The two main essential aspect of metaheuristic algorithms are exploration and exploitation, also known as diversification and intensification respectively [3]. The name diversification and intensification were initially found from the field of Tabu Search. The diversification refers to the skills that a search algorithm applied with the intention to find variety of solutions within different regions of search space, however this process otherwise called global search. Unlike diversification, the intensification refers to the concept that will improve the search process to find a better solution, however this process otherwise is called local search. For many metaheuristics, they need to address exploration and exploitation in a search space; if the balance of both exploration and exploitation are achieved, the performance of its implementation will improve [3], [9]. In
the literature [7], it is reported that balance between the exploration and exploitation is achieved by contribution from both aspects, one of which contributes by quickly identifying region in the search space with high quality solution whilst the other one contributes by identifying the region in the search space from those that are either explored or does not provide high quality solution. Sometimes this balance is not consistence to, as such, several researchers put more efforts to fill the missing gaps, and one of these efforts is the use of metrics (example is dimension-wise diversity measurement) to measure the level of exploration and exploitation [3].

The main aim of each metaheuristic is to gain success in the exploration and exploitation when solving any optimization problem including combinatorial t-way optimization problem. Also, these aspects are closely related as one is known to adjust the speed of convergence for achieving global optima and the other one shadows the other by increase in the probability of finding region in search space where the global optima are located. It was reported in the work [10] that all the metaheuristic algorithms have good performance and simplicity for implementation; also, they have been explored, improved, and widely applied to several problems particularly in fields of science, finance, and engineering. Nevertheless, there is no one single algorithm that work well for every optimization problem [11]. For this reason, research into metaheuristics is still appropriate.

III. COMBINATORIAL T-WAY OPTIMIZATION PROBLEM

In software testing, test case means a set of condition which is intended to verify the functionality of a completed software configuration system. One challenge in this area is combinatorial explosion problem which always intended to find the most optimal final test suite that will cover all combinations of a given interaction strength. As such, test case generation is selected as the most active research area in combinatorial t-way testing as NP-hard [12].

Problem definition

Suppose that the software system under test (SUT) contains n factors called parameters and each parameter pi has ai values (1 ≤ i ≤ n) that can be covered all t interactions associated with subsets in R. For instance, let us consider a given SUT with n parameters, a pairwise final test suite should cover |R| = nx(n-1)/2 different 2-way interactions and R = {pi1, pi2} pi1 ∈ P where i≠j, and then an N-way final test suite cover |R| = Cn⁰ different N-way interactions and R = {pi1, pi2, pi3, ..., piN} pi1, pi2, pi3, ..., piN ∈ P.

Definition 2: The subset ri ∈ R (k=1, 2, 3, ..., t) is an interaction coverage, and the collection R is the interaction relationship of SUT. For simplicity, we support that:

1. Each coverage requirement rk = {pi1, pi2, pi3, ..., pnk} nk ∈ R (k=1, 2, 3, ..., t) has nk parameters where nk > 1.
2. Also, for any two requirements ri1, ri2 ∈ R (k1≠k2), ri1 is not subset of ri2 and vice versa.
3. Two parameters pi, pj ∈ P (i≠j) interact together only if there is a coverage requirement ri ∈ R that pi, pj ∈ ri.

Definition 3: Given A = (aij)nxn as an m×n array, where the j-th column represents the parameter pj of the SUT and all the values of this parameter are finite set as Vj, j=1, 2, 3, ..., n, that is aij ∈ Vj. If there is an nxn sub-array Ai, which comprised the columns of A comparable to the parameter’s interaction coverage requirement mk ∈ R will contain all nk-way values combinations of parameters in mk. More so, we say that A covers the interaction coverage requirement mk and if A satisfies all coverage requirements in R, then we say that A covers the interaction relationship R, and A is a covering array that covers R. However, for a given SUT, the final test suite T that covers interaction relationship R can be acquired in covering array A that covers R.

Definition 4: Let T be a final test suite that covers interaction relationship R of SUT, if it contains minimum size of final test suite, then T is the optimal final test suite that covers R.

By formulating interaction testing as an issue on combinatorial t-way optimization problem definitions, at the end a final test suite will be created that may contain a minimum size and lead to an optimal solution. However, more efforts have been made on t-way testing strategies to adopt nature inspired metaheuristic algorithms for a better optimization in the final test suite.

V. NATURE-INSPIRED METAHEURISTIC ALGORITHMS

In the last 20 years ago, there has been an explosion in the development of new nature-inspired optimization algorithms for solving different problems. The algorithms implemented with an inspiration from nature are called nature-inspired algorithms. This nature inspired algorithms come to be widespread because of their ability to adapt to any changing environment particularly for optimization. Thus, can say nature has inspired too many researchers in different areas
because of its ironic source of inspiration. However, if we look around today, almost all new developed algorithms are nature. In according to the literature [1], [6], [13], for nature inspired algorithms, despite been a metaheuristic category, it is also classified in different level depending on the source of the nature use in the algorithm.

Here, we used sources such as behaviors of living organism in biological term, and physics to classify the nature inspired metaheuristics. Therefore, the rest of the paper will briefly divide all algorithms into different categories of techniques, and we will not claim that one categorization is better than the other, but we will introduce each in the field of optimization problem and stipulate those adopted and not adopted in combinatorial t-way testing for combinatorial explosion problem. Basically, the nature inspired metaheuristics are classified into four categories of technique as shown in Figure 1: Evolution-based, Swarm-based, Human-based, and Physic-based. Even though, Ref. [322] classifies another multi-population method as a nature-inspire metaheuristics which is used purposely to maintain the population diversity by distributing candidate solution on a search space to find global optimization solutions.

**Evolution-based technique**

In this category, all techniques applied are inspired by natural evolution laws [1]. The main idea of this technique is initially started from a set of population generated randomly with determination; next it begins the search process over succeeding generations. After that, the best individuals are collected from all generation and then transferred to the next generation process; this process will continue generation by generation until a condition is met (i.e., when the optimal solution is obtained). The most popular evolution-based algorithm is Genetic Algorithm (GA) that has started becoming popular between 1970’s to 1980’s. GA is used to find optimal solution to the complex optimization problems that would take longer time to solve. It is reported in [15] that GA can work in any search space, because it is regarded as general algorithm. Biologically, GA solutions to a problem are known as chromosomes, whereby the chromosomes make up of more than one characters known as Gene [16], [17]. GA has some advantages from the other metaheuristics as stated in [18]: (1) it uses stochastic operators in searching for a solution that will avoid local optimum, (2) it deals with large parameter spaces, (3) it is easy for implementation, (4) it can handle discrete and continuous parameters, and (5) it can find many solutions in a single run. It the survey literature [16] and another research work [18], all highlighted the main idea of GA, which is based on natural selection and genetics with an inspired operators like selection, crossover, and mutation. The selection operator is used to determine how individuals are selected for breeding which depends on their suitability; the selection operator uses the old population to produce new ones after which a better chromosome is selected for the next generation. Next, the crossover operator is used to applied to the selected chromosome that involves interchanging of genes from the two individuals; crossover operation is repeated to the other next generations. Finally, the mutation operation will be applied to alters the chromosomes to produce good new traits. GA is considered in solving combinatorial optimization problem for software testing (both black box and white box testing) and achieved an optimal solution [16]. Some of the other popular evolution-based algorithms are presented as follows:

De Castro and Timmis in [19] introduced Artificial Immune Algorithm (AIA) as a new computational intelligence approach. The idea of immune system has been taken and abstracted to form basis of the algorithm based on immune system that can be apply in different application areas such as optimization. The working principle in AIA are as follows: the first one is through the combination of antibodies and antigens, while the second one is through the antibody cloning, mutation, selection, and other operations. However, the purpose of AIA is to achieve optimal solution from the antibody and antigen expression problem [20]. According to [21], the AIA is appropriate for solving a multi-objective optimization problem. We have found that AIA been widely used due to its mechanism for the capability of an efficient global search, particularly in areas of artificial intelligence. Yet, there is no t-way strategy that adopt AIA method to construct an optimal test suite for combinatorial optimization problem.

In [22], a new novel optimization method was introduced that inspired by the nature of imperialism called Imperialist Competition Algorithm (ICA). ICA is an evolutionary algorithm that initially start with initial population, where each population individuals is called country as colonies and imperialists that works together to become some empires. ICA creates it basis from the competitions that exist among these empires, in which the weak empires collapse whereas...
the stronger ones take the control of their colonies until there remain only one empire and its colonies that are in the same position as imperialist. The ICA approach is only applied to a few basic optimization problems and four benchmark functions are used to test it. Based on the literature conducted, we have seen some examples of applying ICA method in optimization which include solving non-linear programming problem [23] that used the algorithm to solve the coordination problem of directional overcurrent relays for fault detection. Moreover, ICA is applied to solve problem of unit commitment through sorting of units into different kind of clusters [24]. However, at the present time of this writing there exist no single t-way strategy that adopt to ICA to construct an optimal test suite.

In 2008, Simon persuades the application of mathematics of biogeography in optimization problem to introduced Biogeography Based Optimization (BBO), just like how the mathematics of biological genetics and neuron inspired the development of GA and artificial neural network respectively. The mathematic of biogeography in BBO describe how species migrate from one environment to another environment, new species are produced and become inexistant [25], [26]. BBO can be applied to any problem where GA is used, but there are some special features that BBO has which are unique to GA and other biology-based optimization methods. At the present time of BBO, the author also demonstrates the new method on a real-world sensor selection problem for aircraft engine health estimation that runs successfully. We noticed that BBO is analogue to general problem solution that can be applied to any area of life with the intend of optimization which includes engineering, business, medicine, economics, and so on [26]. Furthermore, BBO is applied to solve a combinatorial problem like Quadratic Assignment Problem [27], but there is no single t-way strategy that adopt to BBO to construct an optimal test suite.

Ecology-inspired Optimization (ECO) evolutionary metaheuristic algorithm has been introduced in [28] that inspired by the natural ecological concepts of habitants. Individual populations (potential solutions to a problem being solved) make up the ECO, and each population evolves according to a search method. Individuals in each population are adjusted in this way according to the mechanisms of intensification and diversification, as well as the initial parameters, which are specific to the search method being used. The only optimization problem addressed by ECO algorithm is numerical optimization problem [28].

The Flower Pollination Algorithm (FPA) metaheuristic has been introduced in [29] that inspired by the natural pollination behavior of flowering plants. The basic of FPA method is the pollination mechanism that occurs when male flower transferring pollen grains to ovules of the female flower via pollinators like butterflies, birds, and bees. FPA was first used to solve the mathematical test functions, and then it was utilized to find the best reservoir operations for downstream water supply and hydropower generation. The authors observed that FPA received widespread attention and been addressed in various optimization problems including power system [30] for economic and dispatch problems, dispatching distribution network problem [31], feature selection problem [32] in data mining, and so on. However, FPA metaheuristic has been adopted around combinatorial t-way testing for test suite generation [33], [34].

Artificial Algae Algorithm (AAA) is introduced [35] recently as a new bio-inspired metaheuristic algorithm. AAA mimics the natural behaviors (movement and adaptation process) of microalgae species. The key idea of AAA method is based on three mechanism of microalgae species, that is the reproduction, adaptation, and their swimming for being closer to light as a photosynthetic organism. However, AAA was precisely designed to solve nonlinear global optimization. AAA has been accepted for solving some optimization problems including multi-objective optimization [36], and binary optimization [37].

Reference [38] recently described a new approach of optimization called Virulence Optimization Algorithm (VOA) which is inspired by the optimal mechanism of viruses when infecting body cells. The essential mechanism of viruses which used by VOA includes the recognition of fittest viruses to infect body cells, reproduction of these cells to prompt “invasion” operation of ready to infect regions and then escaping from infected regions to avoid immune reaction. VOA was designed to solve continuous and non-linear optimization problems. The authors found that VOA has been mentioned in different survey related work such as [39], [40]. However, VOA is yet to be applied to any optimization problem including combinatorial t-way testing.

Monkey King Evolutionary (MKE) as a new metaheuristic algorithm was proposed in [41] mainly to address vehicle fuel consumption optimization problem. MKE key idea is based on natural behavior of monkey king, since he could transform into small monkeys to tackle any dangerous problem arise which implies, he can select a best solution in each space. We have realized that MKE techniques is considered as recently introduced, however it’s only adopted in solving economic dispatch optimization problems [42].

It is worth mentioning that there is other recently developed metaheuristic algorithms motivated by evolution-based techniques, some of the famous ones include: Sun and Leaf Optimization (SLO) introduced in 2018 [43] that inspired by the natural effect of sunlight on the leaves; at the present time of this writing, SLO algorithm is not accepted in any optimization problem. Neural Network Algorithm (NNA) [44] that inspired by biological nervous systems and artificial neural networks; NNA has received widespread attention since its introduction and applied in various field like artificial intelligent problems [45] and engineering optimization problem [46]. Tree Growth Algorithm (TGA) is developed in [47] that inspired by the natural trees
competition for obtaining light and foods; TGA addressed some optimization problems like feature selection problem [48]. In 2020, Seasons Optimization (SO) algorithm is proposed [49] that inspired by the natural growth cycle of trees in different seasons iteratively. In 2020, Coronavirus Optimization Algorithm (COA) is introduced [50] that inspired the reproduction of coronavirus spreads and infecting the healthy people. However, none of these newly evolution-based algorithms were adopted in t-way testing addressing combinatorial optimization problem.

Swarm-based technique

In this category, all techniques applied are inspired by natural social behavior of groups of animals [1]. The main idea of this technique is relating to the collective behavior with some rules in which social insects or animals are adhere to in their normal life activities. For instance, like ants, termites, bees, birds, fish, and so on. The most popular swarm-based algorithm is Ant Colony Optimization (ACO). In the early 1990’s, Ant system algorithm was proposed by Dorigo et al., as an approach to the solution for combinatorial problem. The ACO is one of the earliest metaheuristics, its main idea inspired from the natural behavior of ant in finding shortest paths to the food source. Majority of ants are totally blinded; they cannot see anything, but they have a searching mechanism to find the shortest path to the food. Ant normally communicate and sense their path through what is called pheromone. Pheromone are detected at the tips of ant’s antennae (both left and right) that tell them which way to turn depending on the pheromone strength. The ants move from their nest to the source of food in a search like fashion leaving pheromone trail for other ants to follow [51], [52]. It was reported that ACO as is applied to several combinatorial optimization problem since 1999 in the work of Dorigo [52] the result obtained shows that ACO is very encouraging. Later, ACO taken the attraction of researchers, like in another work of Stizzle & Dorigo in 1999 that addresses traveling salesman optimization problem (TSP), also the result obtained is exceptional when compared to the existing metaheuristics like evolutionary computation or simulated annealing [52]. In 2003, was reported that ACO is one of the most studied population-based method in the combinatorial optimization problem [7]. Some of the other popular swarm-based algorithms are presented as follows:

Reference [53] describe a new metaheuristic method called Bacterial Foraging Optimization Algorithm (BFOA). The key idea of BFOA is the application of social foraging behavior of Escherichia coli bacteria in multi-optimal function optimization. Bacteria search for nutrients in a way to maximize the energy obtained in a time, where individual bacterium communicates with other bacteria by sending signals to them and then the bacterium takes the foraging decisions. BFOA is regarded as a popular global optimization technique for distributed optimization and control. We found that BFOA is mostly applied to areas of data clustering problem for optimization such as the work of [54] [55], and so on. Furthermore, it was adopted in wireless sensor network optimization [56]. However, BFOA is yet to be applied in combinatorial optimization problem for t-way testing strategies.

Cat Swarm Optimization (CSO) that inspired by the natural behavior of cats [57]. The algorithm is based on tracing mode and seeking mode that models the behavior of cats. CSO was used to optimize six test functions using a weighting factor. Our observation to CSO since its proposed, it has received widespread attention and been applied in various optimizations including scheduling problems [58], clustering problems [59], routing problems [60], and so on. To our best knowledge, CSO metaheuristic has not been introduced in combinatorial optimization problem for t-way testing.

Reference [61] described the Ant Bee Colony (ABC) algorithm for optimization based on the behavior of honeybee swarm. In the work, the authors applied the ABC algorithm to optimize multi-variable functions. According to the authors, which stated the main idea of the ABC algorithm in three groups as onlookers, employed bees and scouts. The onlooker is the bee waiting on the dance area for making decision to choose a food source, the employed bee is the bee going to the food source while scout is the bee carrying out random search. However, for each circle there are three prominent steps as follows: (1) to send employed bees onto the food sources and then measure the nectar amount, (2) to select food sources by the onlookers after sharing the information of employed bees and determining the nectar amount of the foods, (3) then to determine the scout bees and then send them on possible food sources. Based on the literature performed, we noted some examples of applying ABC in different areas of optimization includes numerical optimization problem [62], data clustering optimization problem [63], engineering optimization problem [64], and so on. Moreover, ABC has been accepted in solving combinatorial t-way optimization problem [65] [66] [67] [68] [69] [70] [71] [72].

Reference [73] defined a new metaheuristic approach known as Cuckoo Search (CS) that is based on some behavior of cuckoo species and levy flight of some birth and fruit flies. The key idea of CS is built on the following three rules: (1) Each cuckoo lays one egg at a time and dump its egg in randomly chosen nest; (2) The best nests with high quality of eggs will carry over to the next generations; (3) The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird under probability. CS was initially validated against test functions and then compare it to genetic algorithms and particle swarm optimization for performance. We observed that from a quick time. CS was taken much attention of researchers for dealing with different optimization problems such as to reduce the fuel cost [74], economic load dispatch [75], scheduling optimization [76], 5G heterogeneous network selecting and
resource allocation [77]. Moreover, the CS is adopted in some research works to solve the combinatorial optimization problem for t-way testing [78] [79].

Termite Colony Optimization (TCO) metaheuristic algorithm has been introduced [80] that inspired from natural and intelligent behavior of termites. The TCO idea is the mechanism in termites since termites normally move at random in the search space and their paths are subjective toward the regions with more pheromones. The algorithm is mainly designed to solve optimization problem related to numerical functions. Optimization problems addressed by TCO method are not far, even though it’s introduced in wireless network routing problem [81].

Bat Algorithm (BA) is introduced by Yang [82] that is based on the echolocation behavior of bats. The key idea of BA is the capability of echolocation of microbats is fascinating as they can find their prey and differentiate different types of insects/food even in the darkness time with some magic way. For benchmarking, the author has chosen the well-known Rosenbrock’s function with an efficient result. Considering this concept, we have realized that BA has been accepted widely for addressing optimization problems including network scheduling [83], numerical optimization [84], power dispatch [85], power flow [86], and so on. Furthermore, BA has been adopted in solving combinatorial t-way optimization problem [87] [88] [89].

In [90], a new optimization algorithm is developed based on the flashlight of firefly known as Firefly Algorithm (FA). The main idea in the FA is that there are two significant issues: the variation of light intensity and formulation of the attractiveness found between fireflies since the attractiveness of a firefly is determined by its brightness or light intensity which in turn is associated with the encoded objective functions. FA was created to overcome challenges in nonlinear design. Considering this concept, we noticed that FA is very effective in addressing a wide range of optimization problem in the following areas big data [91], portfolio optimization [92], vehicle routing [93], and so on. Further, FA has recently applied in combinatorial t-way testing problem to minimize the number of test case [94] [95] [96].

Reference [97] proposed Cockroach Swarm Optimization Algorithm (CSOA). The key idea of creating CSOA is to only solve travel salesman optimization problem. CSOA mimics the biological behavior of cockroach such as grouping living, searching for food, moving-nest, individual equal and so on. However, CSOA has been applied in some few areas of optimization that involve numerical optimization problem [98] for solving multidimensional space function problems. To be specific, CSOA is not use for solving any t-way testing problem even though its mainly for solving travel salesman problem as one of the combinatorial optimization problems.

Migrating Birds Optimization (MBO) techniques is a nature inspired metaheuristic proposed [99] purposely to test quadratic assignment problem. MBO mimics the natural mechanism of V-flight shape of migrating birds. The MBO works frequently in areas dealing with scheduling optimization problems including [100] for production, [101], [102] for flow shop. Moreover, we discovered that MBO is recently accepted in t-way testing such as [103], [104] for combinatorial explosion problem.

Reference [105] proposed a new optimization algorithm called Krill Herd (KH) for solving optimization problem. KH algorithm simulate the herding behavior of krill. Each individual krill must cover a minimum distance from food and the time-dependent position of everyone is expressed in the following factors: (1) movement induced by the presence of other individuals (2) foraging activity, and (3) random diffusion. KH was primarily tested by utilizing benchmark issues to determine the impact of genetic operators. KH algorithm is introduced by many researchers for different optimization problem that includes [106] for solving numerical optimization problem, [107] for solving engineering optimization problem, [108] for solving multi-objective optimization problems, and so on. Based on the author’s knowledge, there is no single t-way testing strategy that adopt the KH algorithm for solving optimization problem.

Reference [109] proposed Social Spiders Optimization (SSO) as a new optimization algorithm that is based on the simulation of cooperative behavior of social spiders. In SSO, individuals emulate a group of spiders that cooperate to others based on some biological laws of cooperative colony. Normally, the SSO algorithm uses two different search spiders as agents either males or females, and everyone is conducted by a set of different evolutionary operators which mimic different cooperative behaviors that are typically found in the colony. Examples of applying SSO method for solving optimization problem are [110] in knapsack problem, [111] in data clustering, [112] in large scale optimization, and so on. At this present time of writing, we realized that no single t-way strategy adopts SSO algorithm for solving combinatorial optimization problem.

In [113] investigated and described a new optimization method called Dolphin Echolocation Optimization (DEO). DEO mimics the social behavior of dolphins hunting in various environment because of their possess smartness and intelligence. DEO was created based on the amount of computational work that the user may devote to his optimization. Considering this concept, DEO has been very successful in addressing a wide range of engineering optimization problems like [114] [115] [116] for frame design optimization. Nevertheless, the DEO algorithm is not adopted in any t-way testing strategy for solving combinatorial optimization problems.

In [117] present a new metaheuristic optimization algorithm named Symbiotic Organisms Search (SOS) that simulates the symbiotic interaction strategies adopted by organisms to survive and propagate in the ecosystem. To find
the best global solution, the suggested SOS iteratively applies a population of candidate solutions to promising places in the search space. SOS starts with a population known as the ecosystem. A set of organisms is randomly produced to the search space in the first environment. Each organism represents a potential solution to the problem at hand. Each organism in the ecosystem has a fitness value assigned to it, which shows the degree of adaptation to the desired goal. Initially SOS was proposed to be applied to numerical optimization and engineering design problem only but later have been applied to some area for solving optimization problems like the work of [118] in cloud computing, [119] for optimal feature selection in brain computer interface and so on. To be specific, we observed that SOS is not applied to any combinatorial t-way strategy for optimization.

Chicken Swarm Optimization (CSO) as a metaheuristic is introduced in [120] that mimics the natural behavior of chicken swarm. CSO replicates the chicken swarm’s hierarchical organization as well as its behaviors. The swarm of chickens can be separated into numerous groups, each with one rooster and many hens and chicks. Different laws of motion apply to different chickens. Under a specific hierarchical order, there are competitions between different chickens. CSO was designed to solve multi-objective optimization problems. CSO algorithm received some attention and been applied in solving routing optimization problems [121], but it’s yet to be applied in t-way testing for combinatorial optimization.

In [122] described the new metaheuristic approach called Spider Monkey Optimization Algorithm (SMO) mainly for solving numerical optimization problem. SMO mimics the foraging behavior of spider monkeys. Spider monkeys are classified as fission–fusion social structure-based animals. The animals which follow fission–fusion social systems, split themselves from large to smaller groups and vice-versa based on the scarcity or availability of food. Based on the literature conducted, we found that SMO been applied to areas for optimization like constrained optimization problem [123], travel salesman problem [124], data clustering [125], and so on.

Reference [126] investigated and introduced a new metaheuristic algorithm called Whale Optimization Algorithm (WOA) that is inspired by nature. WOA mimics the social behavior of humpback whales that is inspired by the bubble-net hunting approach. WOA was created with the goal of putting 29 mathematical optimization problems and 6 structural design challenges to the test. It has been proved that WOA is able to solve varieties of optimization problem that includes neural network [127], discrete optimization problem [128], both numerical and engineering problem in [129], and so on. However, WOA is only adopted recently for t-way testing strategy in [130] to solve combinatorial optimization problem.

In [131] present Dragonfly Algorithm (DA) as a new metaheuristic optimization method that originate from the behavior of dragonfly in nature. The main idea in DA is the model of social interaction of dragonflies in navigating, searching for foods, and avoiding enemies when swarming dynamically or statistically. DA was introduced to test several mathematical functions. Considering this concept, we have noticed that DA algorithm works in various areas of optimization such as [132] for dealing with probabilistic economic load dispatch problems, [133] for optimizing power flow in solar system. Still, DA is not applied in any t-way testing for solving combinatorial optimization problem.

Crow Search Algorithm (CSA) [134] is introduced purposely for addressing engineering optimization problem. The CSA mimics the intelligent skills behavior of crows based on their search process in storing and retrieving hidden food. Since its proposed, it has received extensive attention and been applied in some areas of optimization like economic dispatch problems [135], feature selection problems [136], and so on. The authors found CSA metaheuristic has been introduced around combinatorial t-way testing [137].

In [138] Shark Smell Optimization (SSO) inspired the natural behavior of shark, as a superior hunter for searching a prey from it smell sense organ and movement to the odor source. Initially, SSO was created to reduce energy loss while also lowering the cost of reactive power compensation. Despite been introduced as recently, the SSO algorithm has been accepted widely for addressing optimization problems including job scheduling problem in cloud computing [139] and NP hard optimization problem in wireless sensor network [140]. However, SSO is not accepted in combinatorial optimization problem for t-way testing.

The authors [141] described the new metaheuristic technique called Ant Lion Optimization Algorithm (ALOA). The key idea on ALOA method is that it mimics the natural hunting behavior of ant lions. By moving in a circular motion and flinging sand out with its huge jaw, an ant lion larva creates a cone-shaped pit in the sand. The larva hides beneath the bottom of the cone after digging the trap and waits for insects to be captured in the pit. The pointed edge of the cone allows insects to readily fall to the bottom of the trap. When the ant lion discovers a prey in the trap, it strives to capture it. Then it’s sucked into the ground and eaten. Ant lions dump the remnants outside the pit after eating the prey and prepare the pit for the next hunt. Initially, ALOA is presented to optimize the location and sizing of distributed generation in radial distribution systems. However, some research accepted the ALOA method in some areas of optimization such as data clustering problem [142], economic dispatch optimization problems [143], simulation optimization problems [144], and so on. At the present time of this writing, no single t-way testing strategy accepted ALOA technique for combinatorial optimization problem.

The authors [145] presented a new metaheuristic optimization method that inspired the natural behavior of spotted hyenas, this algorithm is known as Spotted Hyena
Optimization (SHO). The key idea of SHO method is based on the social relationship amongst spotted hyenas which are comprises in three steps, these are: searching for prey, encircling, and attacking prey. SHO algorithm is presented to solve engineering design problems. However, this new method was attracted by researchers, as such it’s applied in some areas addressing the optimization problems including nonlinear constrained problems [146], automobile optimization problems [147], neural network optimization problems [148], and so on. We observed that SHO is not yet accommodated in t-way testing for tackling combinatorial optimization problem.

The authors [149] introduced the Ideology Algorithm (IA) for solving optimization problems. IA is a metaheuristic technique that inspired by the natural egotistic and competitive behavior of political party individuals. This new technique is yet to attract researchers in addressing any optimization problem, however, at the present time of IA, the technique is applied in solving unconstraint test optimization problem only.

Reference [150] proposed a nature inspired metaheuristic algorithm known as Grasshopper Optimization Algorithm (GOA) purposely to solve structural optimization problem. GOA method mimics the natural behavior of grasshopper swarms through its slow movement and small steps. Another key trait of grasshopper swarming is the search for food sources. Nature-inspired algorithms logically divide the search process into two tendencies: exploration and exploitation. The search agents are urged to move quickly during exploration, while they tend to move slowly during exploitation. However, GOA is not adopted in combinatorial t-way testing problem, even though it is accepted in some areas of optimization including multi-objective problems [151], routing problems [152], scheduling problem [153], and so on.

It is worth mentioning that there is other recently developed metaheuristic algorithms motivated by swarm-based techniques, some of the famous ones include: Coyote Optimization Algorithm (COA) inspired on the Canis latrans species [11], Sea Lion Optimization (SloO) algorithm inspired by the natural hunting behavior of sea lions’ whiskers [154], Butterfly Optimization Algorithm (BOA) inspired natural behavior of butterflies for food search and mating [155], Monarch Butterfly Optimization (MBO) inspired the natural migration skills of monarch butterflies [156], SailFish Optimizer (SFO) inspired by the natural hunting skills of sailfish [157], Emperor Penguins Colony (EPC) mimics the natural behavior of emperor penguins [158], Manta Ray Foraging Optimization Algorithm (MRFOA) inspired from the natural behavior of manta rays based on three foraging strategies [159], Tunicate Swarm Algorithm (TSA) inspired the behavior of tunicates [160], Black Widow Optimization Algorithm (BWOA) that mimics the social courtship behavior of black widow spiders [161], African Vultures Optimization Algorithm (AVOA) inspired by the natural behavior of African vultures for foraging and navigation [162], Red Colobuses Monkey (RCM) algorithm mimics the natural behavior of red monkeys [163], Rock Hyraxes Swarm Optimization (RHSO) inspired by the natural behavior of rock hyraxes swarms [164], Artificial Gorilla Troops Optimizer (GTO) inspired by the natural gorilla troops’ social intelligence [165], Ebola Optimization search Algorithm (EOSA) mimics the natural propagation mechanism of Ebola virus disease [166], Dingo Optimizer (DOX) that inspired by the social behavior of dingo [167], Honey Badger Algorithm (HBA) inspired the natural foraging behavior of honey badger [168], and so on. However, none of these newly swarm-based algorithms were adopted in t-way testing addressing combinatorial optimization problem.

**Human-based technique**

In this category, all techniques applied are inspired by natural behavior of humans [1]. The main idea of this technique is relating to the improvement in level of searching which is done by human being. The most popular human-based algorithm is Tabu Search (TS). It was reported in the research work of TS was proposed by Fred W. Glover in the late 1980’s to solve optimization problem which are difficult, because by then the existing heuristic techniques suffered from solving local optima problem [169] [170] [171]. TS is one of the oldest metaheuristics that adapt to adaptive programming to solve different field of optimization problems [169]. This adaptive procedure can use different methods such as linear programming algorithm and specialized heuristics that overcome the limitation of local optimality [170]. Over the past decade, many researchers worked to improve the TS to find the near optimal solution for a specified problem [171]. According to [169] which gives the basic concept of TB in three defined schemes: (1) the use of flexible memory for searching and evaluating the information of the past moves with are performed on the solution; (2) controlling the present moves which are applied on the solution during searching process; (3) the use of memory function in different time. The memory structure used in TS are roughly divided into three classes: short-term, intermediate-term and long-term. The TS algorithm is different from other metaheuristics, it starts from single solution and move to the final optimal solution [169], [171]. In TS current solution is randomly selected from which neighbor solution stored, while the best solution is obtained depending on the objective function. TS start from single solution and storing the best solution in the memory from each move. This is how TS overcome the problem of local optima faced by other heuristic techniques [169], [171]. Some of the other popular human-based algorithms are presented as follows:

Reference [172]. The idea of Harmony search was as a result in listening to a piece of traditional music, at that time no one knows if connection of a music can has finding to an
optimization. It has been long and for the first time ever that a top scientist creates such an interesting idea by developing a new metaheuristic algorithm known as Harmony Search (HS). The secret behind HS has been borrowed from the musician when harmony is composed. As we know, a musician normally has lot of music pitch in their memory, they always try different possible combinations of the music pitches which is stored in their memory. HS was inspired by the remark that the main target of any music is to search and play for a perfect state of harmony. Since its introduction in 2001, HS has been used to tackle water distribution network problems. Considering this concept, the algorithm works satisfactorily in different optimization fields including but not limited to engineering optimization problem [173], scheduling optimization problem [174], numerical optimization problem [175]. To be specific, HS is adopted in t-way testing strategies for solving combinatorial optimization problem [176] [177] [178] [179] [180] [181].

In [182] proposed a new metaheuristic called League Championship Algorithm mainly for solving numerical function optimization problem. LCA inspired by the competition of sport teams plays in a sport league. Several individuals refer to as sport teams that compete in an artificial league for a week after another (repeatedly). Built from the league match timetable in each week, teams are play in pairs with a condition to win or lose, given known the team’s playing strength (fitness value) resultant from a particular team formation. In the recovery time, each team organizes a new change in the playing style (a new solution) for the next week match and the championship will continue for several seasons (stopping condition). To be specific, LCA is adopted [183] [184] in cloud computing for solving scheduling optimization problem, based on the iterative process for solving the global optimization problem [185]. However, LCA algorithm has not been accepted for t-way testing strategies in solving combinatorial optimization problem.

Reference [186] present the Seeker Optimization Algorithm (SOA) as a new metaheuristic for solving optimization problem related to reactive power dispatch. The SOA is based on the concept of mimicking the act of human searching, where the search direction is based on the empirical gradient by evaluating the response to the position changes and the step length is based on uncertainty reasoning by using a simple Fuzzy rule. The authors then applied SOA to reactive power dispatch on standard IEEE 57 and 118 bus power systems for optimization. Similarly, it was applied in some areas of optimization as well such as constrained optimization problem [187], optimization problem associated to power system [188], engineering problem [189], and so on. Yet, we have seen SOA not appropriate in any t-way testing for solving combinatorial optimization problem.

Consultant Guided Search (CGS) algorithm inspired by the idea people used to follow decisions from consultants [190]. CGS is a method that is based on a population. A member of the CGS population is a virtual person who may operate as both a client and a consultant at the same time. A virtual person acts as a customer, constructing a solution to the problem at each iteration. A virtual person who works as a consultant gives clients advise to assist them in developing a solution. The algorithm keeps track of the best outcome obtained by any client working under their direction for each consultant. CGS technique is mainly introduced for addressing combinatorial optimization problem only, however it’s not yet adopted in t-way testing.

In [191], the authors described the Group Counseling Optimization (GCO). GCO mimics the group counseling behavior of humans in solving their day-to-day problems. The key idea of GCO is how people with problems are seeking out another person as a sounding board: someone with whom they can talk over their problems, experiment with various solutions, and finally reach some resolution. GCO is first put to the test with seven unrotated benchmark functions and five rotated benchmark functions. GCO is not rarely apply in solving optimization problem, even though in [192] used GCO for solving single-objective optimization problem. To the author’s knowledge, GCO is not adopted by any t-way testing strategy for solving combinatorial optimization problem.

The Anarchic Society Optimization (ASO) algorithm [193] is inspired by the natural social behavior of grouping where members behave anarchically. The members of ASO are unpredictable, and their unpredictability grows as their position worsens. They also act irrationally and recklessly, heading toward the lower positions they’ve already visited. ASO can search the solution space perfectly and avoid falling into local optimum traps by using these anarchic members. Since its proposed, it hasn’t been used in combinatorial t-way testing, even though it received a little attention and been applied only in water resources management optimization problem [194].

Reference [195] proposed a metaheuristic method mainly for solving constrained mechanical design problems, this method known as Teaching Learning Based Optimization (TLBO). TLBO is a nature-inspired algorithms that mimics the effect of influence of a teacher on learners. TLBO process is categorized into two phases: the teacher phase that will assist in learning from the teacher; the learner phase that will assist in learning by collaboration among learners. TLBO method provide output of learners based on the effect of the influence of a teacher. The output is the results or grades obtained from learners since teachers are considered as a highly learned person who shares knowledge to learners. However, the quality of a teacher will impact the learner’s outcome. With time, TLBO has been accepted widely for addressing different optimization problems such as numerical and engineering [196], knapsack optimization [197], route optimization [198], and so on. Similarly, TLBO method was adopted in t-way testing strategy to solve combinatorial
optimization problem in the works of [199] for mixed strength t-way test suites, and [200] for pairwise testing.

Mine Blast Algorithm (MBA) is presented in [201] as a new method of optimization. MBA is a nature inspire algorithm that derived from the explosion of mine bombs in real world, in which shrapnel fragments impact with other mine bombs around the explosion region, causing them to explode. At the time of MBA, it was tested using optimization of several truss structures with discrete variables successfully. Considering this concept, MBA has been applied successfully in addressing a wide range of optimization problem that include engineering problems [202], numerical problems [203], feature selection problems [204], and so on. To be specific, there is no single t-way strategy adopt MBA to solve combinatorial optimization problem.

Reference [205] described a new optimization method entitled Soccer League Competition algorithm (SLC). SLC is a metaheuristic algorithm which produces optimal solution for the design of water distribution network. The key idea here is that SLC inspired from competitions in soccer leagues between teams and their players. SLC methods starts with an initial population (players) which are in two types: fixed players (starting players) and substitutes players that all together form a team. The competition among teams is to top ranked positions in the league table and the internal competitions between players in each team for personal improvements are used for simulation purpose and convergence of the population individuals to the global optimum. Furthermore, SLC is used in some quite number for solving optimizations such as knapsack problem [206], wireless sensor network deployment problem [207], distribution grid problem [208], and so on. However, it was found in the obvious literature that SLC method is not yet apply to any combinatorial optimization problem.

In [209] proposed Exchange Market Algorithm EMA as a new method of optimization. EMA is mainly for solving continuous non-linear optimization problems. EMA is a metaheuristic that inspired by the system procedure of trading the shares on stock market. EMA techniques have two modes, the first mode that there is no oscillation in the market and then the second mode that market has oscillation. However, at the end of each mode the individuals are evaluated. Moreover, EMA`s duty is to recruit people toward successful individuals in the first mode, whereas in the second mode it seeks for optimal points. To be specific, EMA is used in several areas of optimization that includes economic dispatch problem [210] [211], power system problem [212], and so on. Nevertheless, the EMA method is not adopted in any t-way testing strategy for solving combinatorial optimization problems.

In [213] a new optimization algorithm is developed based on interior design and decoration named Interior Search Algorithm (ISA) for global optimization. The method in ISA is divided into two groups except for the fittest element. The first group is called composition group in which the composition of elements is changed to find a more beautiful view; whereas the second group is called mirror group in which mirrors are placed between these elements and the fittest element to find better views. Considering this concept, ISA method have been adopted to solve engineering optimization problem [214], economic dispatch problem [215], power dispatch problem [216]. To the author`s knowledge, there is no single t-way strategy that adopt ISA method for combinatorial optimization.

Reference [217] Colliding Bodies Optimization (CBO) is presented as a new meta-heuristic method for solving numerical problem. The CBO is based on one-dimensional collisions between bodies, with each agent solution being considered as an object or body with mass. After a collision of two moving bodies having specified masses and velocities, these bodies are separated with new velocities. The collision between the bodies causes the agents to move in the direction of better positions. CBO is applied in [218] to solve power flow optimization problem, for global optimization problem [219], and so on. But there is no single t-way strategy that used CBO method to solve combinatorial optimization problem.

Reference [220] introduced Search Group Algorithm (SGA) method to solve truss optimization problems. The fundamental concept of SGA method is divided into two types of iteration, the first iterations of the optimization process try to find promising regions on the defined search boundary, whereas the subsequent iterations refine the best design in each of these promising regions. SGA have been applied to other optimization problems such as power system optimization [221], [222], thermo-economic optimization problem [223], and so on. To the author`s knowledge, SGA is yet to apply in t-way testing strategy for solving combinatorial optimization testing.

Jaya Algorithm (JA) is based on the principle of which solution obtained from a problem is then move towards finding the best solution by avoiding worst solution [224]. By considering this concept, JA has been applied in various optimization field like feature selection optimization problem [225], moreover, the JA metaheuristic has recently been introduced around t-way testing [226].

It is worth mentioning that there are other recently developed metaheuristic algorithms motivated by human-based techniques, some of the famous ones include: Farmland Fertility (FF) algorithm inspired the nature of farmland fertility [227], Queuing Search (QS) algorithm inspired the natural human activities in queuing [228], Supply Demand-based Optimization (SDO) method mimics the demand relation of consumers and supply relation of producers [229], Gaining Sharing Knowledge-based algorithm (GSK) mimics the natural process of gaining and sharing knowledge between human during their life time [230], Interactive Autodidactic School (IAS) technique mimics the basis of interaction occurs among students of
of the other popular physic-based algorithms are presented as follows:

Reference [243] proposed Small World Optimization Algorithm (SWOA) as a method for function optimization that inspired by the process of small world phenomenon. SWOA comprises of two main operators namely the local short range search operator and the random long range search operator. SWOA believes that the search process is a basic of information transmission process in search space networks that both operators provided. SWOA was applied in few areas to address optimizations that include network routing problem [244], automobile sequencing problem [245], neural network problem [246]. At the present time of this writing, SWOA is not adopted to any t-way testing strategy.

In [247] a new optimization method that inspire by the Big Bang and Big Crunch theory of the evolution in the universe is proposed. In this new method, two phases were considered as Big Bang and Big Crunch. However, the key idea of Big Bang phase is the energy dissipation produces disorder and randomness whereas the Big Crunch phase randomly distributed particles in an order. Combining these two phases that forms the construction of this new method called Big Bang-Big Crunch (BB-BC). Considering this concept found that BB-BC was applied mostly in construction engineering design optimization problem [248] [249], also it is used in area like data clustering [250]. But this introduced method is yet to adopt any t-way testing strategy for solving combinatorial optimization problem.

Reference [251] Central Force Optimization (CFO) algorithm was presented to solve optimization problem. CFO is a metaheuristic algorithm that is based on the nature of gravitational kinematic (that is motion of masses under the control of gravity). CFO has been very successful in addressing a small range of optimization problems such as data clustering problem [252], image processing problem [253], and so on. To the author’s best knowledge, CFO techniques is not used in t-way testing.

Gravitational Search Algorithm (GSA) was introduced by [254] based on the law of gravity and mass interactions for optimization. In GSA method, the search agents are set of masses that work together based on the Newtonian gravity and the laws of motion. The GSA method is a specific to solve nonlinear functions. However, it has been accepted widely in different optimization problems, some of them are binary encoded optimization problem [255], scheduling optimization problem in cloud computing [256], wireless sensor optimization problem to optimizes the coverage and connectivity of a network [257], and so on. However, GSA was recently adopted in t-way testing strategy [258], [259] to construct an optimal test suite.

In [260] proposed a new metaheuristic approach known as Randomized Gravitational Emulation Search Algorithm (RGES) particularly to solve a large size set covering problems. RGES algorithm mimics the law of gravity (randomization concept along with velocity and gravity

Physic-based technique

In this category, all techniques applied are inspired by the physical rules in the universe [1]. The main idea of this technique is motivated by imitating a particular physical or chemical law such as electrical charges, gravity, river systems, chemical reactions, and so on. The most popular Physic-based algorithm is Simulated Annealing (SA). SA is one of the oldest and popular local search metaheuristics that originated from statistical mechanics. SA is named after its resemblance to the process of physical annealing with solids. Here, crystalline solid is heated then let it to cool slowly until it solidifies into ideal crystalline structure. So, the simulation of this process is called simulated annealing [240]. The research work of [241], summarized SA process in two basic steps as: (1) To bring the solid to a very high temperature until melting of the structure; (2) To cool the solid according to a very particular temperature decreasing scheme to reach a solid state of minimum energy. According to [240], SA is a modification of Metropolis algorithm in which temperatures are changing from higher state to lower state. Also, highlighted that SA is fundamentally comprised of two stochastic methods: the first method for the generation of solutions while the other method for the acceptance of solutions. The concept in SA is by iteration, from each iteration the SA algorithm is applied to a discrete optimization problem, then the values of the current and new solution are compared [242]. On the later time, SA was first presented as a method for solving combinatorial optimization problem in 1980’s by Kirkpatrick and his co. [7] [241]. Some

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parameters) in physics nature. RGES have not been popular, even though it is adopted in data clustering problems [261].

Reference [262] introduced a new metaheuristic is named Galaxy-based Search Algorithm (GbSA) for continuous optimization problem. The GbSA mimics the spiral arm of spiral galaxies to search its surrounding. This spiral movement is enhanced by chaos to escape from local optimums. GbSA has been very successful in addressing a few areas of optimization like economic and dispatch problem [263], travelling salesman problem [264]. To the author’s knowledge, GbSA is not use in t-way testing strategy for combinatorial optimization problem.

In [265] Eskandar et al., introduced a new metaheuristic technique called Water Cycle Algorithm (WCA) primarily for solving constrained optimization and engineering design problems. The key idea of WCA is that inspiration of nature based on the observation of water cycle process and how rivers and streams flow to the sea. The WCA method starts with a population known as the raindrops. It is assumed, first and foremost, that there will be rain or precipitation. As a sea, the best individual (best raindrop) is chosen. Then a few good raindrops are picked to form a river, while the remainder of the raindrops become streams that flow into rivers and the sea. Considering this concept, WCA techniques addresses the optimizations in some areas such as travelling salesman problem [266], data clustering problem [267], linear and nonlinear ration problem [268], and so on. However, WCA is not use in t-way testing strategy problem.

In [269] a new metaheuristic method called Ray Optimization (RO) was introduced to address the near-global optimum in optimization problems. RO mimics the natural comportment of ray, that is when light travels from a lighter lane to a darker lane it refracts and its direction changes (Snell’s light refraction law). The ray transition is used to discover the global or near-global solution in this case. However, we observed RO method is used in some quite number of optimizations like economic generation scheduling problem [270]. To be specific, RO is not adopted in t-way testing strategy problem.

Reference [271] proposed a chemistry-based metaheuristic algorithm called Artificial Chemical Reaction Optimization Algorithm (ACROA) for global optimization. ACROA inspire from chemical reaction in which reactants are selected based on their concentration. There are two types of reaction in ACROA method which are consecutive reaction and competing reaction, whereas the output of reaction can be the input of another reaction. ACROA starts with a solution of basic reactants. Chemical reactions are then used to consume and produce reactants. When the termination criterion is reached, the algorithm is terminated, like when no more reactions may occur (inert solution). ACROA has addresses some optimization that include the NP hard problem [272], clustering problem [273], and so on. ACROA is not devoted in t-way testing strategy problem.

Black Hole Algorithm (BHA) is inspired by the black hole situation in nature [274] and presented as a nonlinear problem solution. The black hole is simulated in BHA by the agent with the best solution. Any agent within the event horizon vanishes and is re-initialized in the search space after the event horizon is calculated. Since its proposed, it has received widespread attention and been applied in various optimizations including scheduling problems [275], data clustering problem [276], and so on. However, we noticed the BHA technique been introduced recently into t-way testing [277].

In [278] Grey Wolf Optimizer Algorithm (GWO) is proposed to solve three classical engineering design problems. GWO is a metaheuristic that mimics the natural leadership hierarchy and hunting mechanism of grey wolves (that is alpha, beta, delta, and omega). GWO method includes three main steps for the hunting mechanism as searching for prey, encircling prey, and attacking prey. GWO is used in some areas like economic dispatch optimization [279], numerical optimization [280], power scheduling optimization [281], and so on. However, the authors investigate that GWO algorithm is not yet applied to any t-way testing strategy for addressing combinatorial optimization problem.

Vortex Search Algorithm (VSA) is regarded as a powerful one-solution-based metaheuristic algorithm proposed to solve numerical optimization problem [282]. VSA method inspired the nature of vortex shape produced by vortical flow of stirred liquids. In two-dimensional space, vortex patterns can be represented as a collection of layered circuits. The starting circuit of the search space is the largest and most outside circuit. As a result, a fair balance of explorative and exploitative search behavior is achieved. We have realized that VSA has less attraction to many areas of optimization, even though it was recently accepted in solving neural network problem [283], but its yet to be adopted in t-way testing.

Lightning Search Algorithm (LSA) is based on the principle of lightning by nature [284] for solving constraint optimization problems. LSA can be thought of as a step leader propagation mechanism in its broadest sense. Instead, of using the concept of streamers, it considers the participation of rapid particles known as projectiles in the construction of the step leader’s binary tree structure and the simultaneous formation of two leader tips at fork points. Since its proposed, it has received little attention and been applied in economic dispatch optimization problem [285].

Reference [286] introduced the General Relatively Search Algorithm (GRSA) for global optimization. GRSA inspired by general relativity theory in physics that considered a population of particles in a search space. The basic idea of GRSA is general relativity theory that contain particles (agents) moving along the geodesic trajectories in a curved space, moreover these particles are updated using velocity and geodesics in solving optimization problem to move toward the optimal point. We realized that GRSA is regard as
recently proposed, as such no attention is given to the method.

Optics Inspired Optimization (OIO) was introduced [287] recently as new physic inspired metaheuristic method primarily for solving numerical optimization problem. OIO metaphor is optical phenomena based on the law of reflection from physics of optics. The key idea of adopting law of reflection in OIO is the concave reflecting surface and convex surface that causes the incident light rays to converge and reflect away respectively, so that they all appear to be diverging. However, OIO algorithm is applied in quite number of areas for optimization, these are travelling tournament problem [288] and truss optimum design problems [289].

Reference [290] recently described the Water Wave Optimization (WWO) metaheuristic algorithm for global optimization problems. WWO inspired by the shallow water wave theory with the following phenomena: propagation, refraction, and breaking, all to derive the effectiveness for searching in a high-dimensional solution space. Considering this concept, WWO have been devoted in addressing optimizations such as route optimization problems [291], power dispatch problems [292], data clustering problems [293], and so on. Moreover, WWO techniques used in addressing some combinatorial optimization problems [294], however its yet to be adopted in t-way testing strategy.

Sine Cosine Algorithm (SCA) is based on the principle of sine cosine functions to find a best solution [295]. SCA approaches begin the optimization process by generating several random solutions, which are then assessed repeatedly by an objective function and improved by a set of rules that form the core of the optimization technique. The SCA techniques search for optimization issue optimu in a stochastic manner, but there is no assurance that a solution will be found in a single run. However, the likelihood of obtaining the global optimum improves as the number of random solutions and optimization stages (iterations) grows. The SCA algorithm is very specific at addressing constrained and unknown search spaces in real-world applications. Since its proposed, it has received widespread attention and been applied in various optimization like routing problem [296], feature selection problem [297], and so on. Moreover, SCA metaheuristic has been introduced around t-way testing [298] [299] for combinatorial optimization problem.

Water Evaporation Optimization (WEO) [300] is a nature inspired metaheuristic algorithm specifically for global optimization problems. WEO algorithm mimics the rules regulating the evaporation process of a small amount of water molecules on the wettability solid surface. It is well known, based on molecular dynamics simulations, that as the surface changes from hydrophobicity to hydrophilic, the evaporation speed does not decrease monotonically as one might expect, but instead increases first, then drops after reaching a maximum value. When the substrate's surface wettability is insufficient, water molecules condense into a sessile spherical cap. The geometry shape of the water congregation is the most important component that determines evaporation speed. We noted that WEO algorithm is adopted only in few areas of optimization like the constrained problems [301].

Thermal Exchange Optimization (TEO) algorithm inspired the Newton’s law of cooling [302]. Each agent in TEO is regarded a cooling object, and heat transfer and thermal exchanging occur between them when they are joined as a surrounding fluid by another agent. Each agent's new temperature is determined by its new position in the search space. Since its proposed, it has received a little attention and been applied in some areas like constrained nonlinear optimization problem [303], image fusion problems [304], and so on.

It is worth mentioning that there are other recently developed metaheuristic algorithms motivated by physics-based techniques including Atom Search Optimization (ASO) [305] that mimics the nature of atomic motion model, Algorithm of the Innovative Gunner (AIG) [306] that inspired the choice of artillery parameters, Projectiles Optimization (PRO) algorithm [307] that inspired by models in kinematics, Gradient-Based Optimizer (GBO) [308] that inspired by the gradient-based Newton’s method, Dynamic Differential Annealed Optimization (DDAO) [309] that mimics the current technique in producing high-quality steel, Lévy Flight Distribution (LFD) [310] that inspired from the Lévy flight, Solar System Algorithm (SSA) [311] that mimics the natural behavior of some objects around solar system, Archimedes Optimization Algorithm (AOA) [312] that inspired the law of Archimedes’ Principle in physics, Material Generation Algorithm (MGA) [313] that mimics the basic aspects of material chemistry, Crystal Structure Algorithm (CryStAl) [314] that inspired by the basic principles of crystal structures formation, Gamma Ray Interactions Based Optimization (GRIBO) [315] that mimics various energy loss processes of gamma ray. However, these newly physic-based techniques are yet to be adopted in t-way testing problem.

VI. RESULT

This section addresses the nature-inspired metaheuristics with their relatively current state of use and new suggestions for possible future research opportunities in the field of combinatorial t-way testing. In the last two decades, nature inspired metaheuristic algorithms shows an incredible contribution for various optimization problem solving methods. As such, several comprehensive research of nature-based is coming up in a big way to further enhance the optimization methods. Additionally, the effectiveness of these nature-based techniques to solve various optimization problems have been summarized and classified the techniques into four classes as depicted in Figure 1: evolution-based, swarm-based, human-based, and physics-based. However, we reviewed a distinguished one hundred
and ten (110) outstanding nature inspired metaheuristic algorithms of the last two decades (2001 to 2021) from these various nature-based classifications with their respective current state of use to inspire future research in the field of combinatorial t-way testing.

From this review work, we found that not all the metaheuristics are defined effectively adopted in combinatorial t-way testing, some proved to be very effective and thus have been popular methods selected whilst others are ineffectually adopted. For instance, from the popularly known metaheuristics like GA which was adopted in [316] for t-way testing to address combinatorial optimization problem while BFOA [53] is still yet to be adopted. Therefore, we are going to explore our discussions in the following subsections:

A. ASSESSMENT BY CLASSIFICATION

To examine these algorithms, we first attempt to compare their classifications. Table 1 provides a comparison of the algorithms count reviewed in the current paper write-up from the various techniques which are enlisted in Table 1.

| S/N | Technique | Count | Percentage |
|-----|-----------|-------|------------|
| 1   | Evolution-based | 13    | 12%        |
| 2   | Swarm-based     | 39    | 36%        |
| 3   | Human-based     | 28    | 25%        |
| 4   | Physic-based    | 30    | 27%        |

In a nutshell, we can say that most of these new generation metaheuristic algorithms reviewed in this study are 36% belongs to swarm-based, then 27% belong to physic-based, then 25% belongs to human-based and 12% belongs to evolution-based. Having such assessment, we can conclude that swarm-based technique dominated nature-inspired metaheuristic method. Meanwhile, the natural social behavior of groups of animals is more suitable for solving various optimization problem.

B. EVOLUTION-BASED TECHNIQUE ANALYSIS.

Table 2 represents the evolution-based techniques assessment developed in between 2001 and 2021, the algorithm names, their abbreviations, year of invention and their state-of-use whether adopted in combinatorial t-way optimization or not. In this period of 20 years, thirteen (13) evolution-based algorithms are developed according to the best of author’s knowledge. However, there is a rapid increment of the algorithms in that period, but with less adoption to combinatorial t-way optimization.

| S/N | Algorithm          | Abbreviation | Year | Combinatorial t-way optimization adopted | Not adopted |
|-----|--------------------|--------------|------|------------------------------------------|-------------|
| 1   | Artificial Immune Algorithm | AIA          | 2002 | ✓                                        |             |
| 2   | Imperialist Competitive Algorithm | ICA         | 2007 | ✓                                        |             |
| 3   | Biogeography Based Optimizer      | BBO         | 2008 | ✓                                        |             |
| 4   | Ecology-inspired Optimization       | ECO         | 2011 | ✓                                        |             |
| 5   | Flower Pollination Algorithm    | FPA          | 2012 | ✓                                        |             |
| 6   | Artificial Algae Algorithm        | AAA          | 2015 | ✓                                        |             |
| 7   | Virulence Optimization Algorithm | VOA         | 2016 | ✓                                        |             |
| 8   | Monkey King Evolutionary Algorithm | MKE        | 2016 | ✓                                        |             |
| 9   | Sun and Leaf Optimization          | SLO          | 2018 | ✓                                        |             |
| 10  | Neural Network Algorithm          | NNA          | 2018 | ✓                                        |             |
| 11  | Tree Growth Algorithm             | TGA          | 2018 | ✓                                        |             |
| 12  | Seasons Optimization Algorithm    | SO           | 2020 | ✓                                        |             |
| 13  | Coronavirus Optimization Algorithm | COA        | 2020 | ✓                                        |             |

Figure 2 demonstrates the combinatorial t-way adoption of evolution-based techniques for optimization in the last two decades. It can be easily seen that all algorithms are not adopted in combinatorial t-way optimization, only one algorithm was adopted between 2011 and 2015 range.
From the analysis above, it can be said that out of the thirteen (13) algorithms only one (1) is adopted in combinatorial t-way optimizations, whereas others are not.

C. SWARM-BASED TECHNIQUE ANALYSIS

Table 3 represents the swarm-based techniques assessment developed in between 2001 and 2021, the algorithm names, their abbreviations, year of invention and their state-of-use whether adopted in combinatorial t-way optimization or not. In this period of 20 years, thirty-nine (39) swarm-based algorithms are developed according to the best of author’s knowledge. Similarly, there is a rapid increment of the algorithms in that period, but with less adoption to combinatorial t-way optimization.

**Table 3: Swarm-based Technique Analysis for Combinatorial T-way Optimization.**

| S/N | Algorithm                              | Abbreviation | Year | Combinatorial t-way optimization |
|-----|----------------------------------------|--------------|------|----------------------------------|
|     |                                        |              |      | Adopted                           | Not adopted |
| 1   | Bacterial Foraging Optimization Algorithm | BFOA         | 2002 | ✓                                |             |
| 2   | Cat Swarm Optimization                 | CSO          | 2006 | ✓                                |             |
| 3   | Artificial Bee Colony                  | ABC          | 2007 | ✓                                |             |
| 4   | Cuckoo Search                          | CS           | 2009 | ✓                                |             |
| 5   | Termite Colony Optimization            | TCO          | 2010 | ✓                                |             |
| 6   | Bat Algorithm                          | BA           | 2010 | ✓                                |             |
| 7   | Firefly Algorithm                      | FA           | 2010 | ✓                                |             |
| 8   | Cockroach Swarm Optimization Algorithm | CSOA         | 2011 | ✓                                |             |
| 9   | Migrating Birds Optimization           | MBO          | 2012 | ✓                                |             |
| 10  | Krill Herd                             | KH           | 2012 | ✓                                |             |
| 11  | Social Spider Optimization             | SSO          | 2013 | ✓                                |             |
| 12  | Dolphin Echolocation Optimization      | DEO          | 2013 | ✓                                |             |
| 13  | Symbiotic Organisms Search             | SOS          | 2014 | ✓                                |             |
| 14  | Chicken Swarm Optimization             | CSO          | 2014 | ✓                                |             |
| 15  | Spider Monkey Optimization             | SMO          | 2014 | ✓                                |             |
| 16  | Whale Optimization Algorithm           | WOA          | 2016 | ✓                                |             |
| 17  | Dragon Flies                           | DF           | 2016 | ✓                                |             |
| 18  | Crow Search Algorithm                  | CSA          | 2016 | ✓                                |             |
| 19  | Shark Smell Optimization               | SSO          | 2016 | ✓                                |             |
| 20  | Ant Lion Optimization Algorithm        | ALOA         | 2016 | ✓                                |             |
| 21  | Spotted Hyena Optimization             | SHO          | 2017 | ✓                                |             |
| 22  | Ideology Algorithm                     | IA           | 2017 | ✓                                |             |
| 23  | Grasshopper Optimization Algorithm     | GOA          | 2017 | ✓                                |             |
| 24  | Coyote Optimization Algorithm          | COA          | 2018 | ✓                                |             |
Figure 3 represents the combinatorial t-way adoption of swarm-based techniques for optimization in the last two decades. It can be easily observed that most of the algorithms are not adopted in combinatorial t-way optimization, only four was adopted between 2006 and 2010 range, one between 2011 and 2015, while two between 2016 and 2020.

In nutshell, we can say that out of the thirty-nine (39) algorithms developed, only seven (7) are adopted in combinatorial t-way optimizations, whereas others are not.

D. HUMAN-BASED TECHNIQUE ANALYSIS

Table 4 demonstrates the human-based techniques assessment developed in between 2001 and 2021, the algorithm names, their abbreviations, year of invention and their state-of-use whether adopted in combinatorial t-way optimization or not. In this decades, twenty-eight (28) human-based algorithms are developed according to the best of author’s knowledge. Likewise, there is a rapid increment of the algorithms in that period, but with less adoption to combinatorial t-way optimization.

| S/N | Algorithm                                | Abbreviation | Year | Combinatorial t-way optimization |
|-----|-----------------------------------------|--------------|------|----------------------------------|
| 1   | Harmony Search                          | HS           | 2001 | ✓                                |
| 2   | League Championship Algorithm           | LCA          | 2009 | ✓                                |
| 3   | Seeker Optimization Algorithm           | SOA          | 2009 | ✓                                |
Figure 4 demonstrates the combinatorial t-way adoption of human-based techniques for optimization in the last two decades. It can be easily seen that almost all the algorithms are not adopted in combinatorial t-way optimization. However, the HS [172] was adopted in 2001 to 2015 range, TLBO [195] in 2011 to 2015, while JA [224] in 2016 to 2020 range.

Therefore, it can be said that out of the twenty-eight (28) algorithms only three (3) are adopted in combinatorial t-way optimizations, whereas others are not.

**E. PHYSICS-BASED TECHNIQUE ANALYSIS**

Table 5 represents the physic-based techniques assessment developed in the last 20 years, the algorithm names, their abbreviations, year of invention and their state-of-use.
whether adopted in combinatorial t-way optimization or not. In this period, thirty (30) physic-based algorithms are developed according to the best of author’s knowledge.

Similarly, there is a rapid increment of the algorithms in that period, but with less adoption to combinatorial t-way optimization.

| S/N | Algorithm                                      | Abbreviation | Year | Combinatorial t-way optimization adopted | Not adopted |
|-----|-----------------------------------------------|--------------|------|-----------------------------------------|-------------|
| 1   | Small World Optimization Algorithm            | SWOA         | 2006 | ✓                                        |             |
| 2   | Big-Bang-Big-Crunch                           | BBBC         | 2006 | ✓                                        |             |
| 3   | Central Force Optimization                    | CFO          | 2007 | ✓                                        |             |
| 4   | Gravitational Search Algorithm                | GSA          | 2009 | ✓                                        |             |
| 5   | Randomized Gravitational Emulation Search Algorithm | RGES     | 2010 | ✓                                        |             |
| 6   | Galaxy-based Search Algorithm                 | GBSA         | 2011 | ✓                                        |             |
| 7   | Water Cycle Algorithm                         | WCA          | 2012 | ❌                                       |             |
| 8   | Ray Optimization                              | RO           | 2012 | ✓                                        |             |
| 9   | Artificial Chemical Reaction Optimization Algorithm | ACROA | 2012 | ✓                                        |             |
| 10  | Black Hole Algorithm                          | BHA          | 2013 | ✓                                        |             |
| 11  | Grey Wolf Optimizer Algorithm                  | GWOA         | 2014 | ✓                                        |             |
| 12  | Vortex Search Algorithm                       | VSA          | 2015 | ✓                                        |             |
| 13  | Lightning Search Algorithm                    | LSA          | 2015 | ✓                                        |             |
| 14  | General Relativity Search Algorithm           | GRSA         | 2015 | ✓                                        |             |
| 15  | Optics Inspired Optimization                  | OIO          | 2015 | ✓                                        |             |
| 16  | Water Wave Optimization                       | WWC          | 2015 | ✓                                        |             |
| 17  | Sine Cosine Algorithm                         | SCA          | 2016 | ✓                                        |             |
| 18  | Water Evaporation Optimization                | WEO          | 2016 | ✓                                        |             |
| 19  | Thermal Exchange Optimization                 | TEO          | 2017 | ✓                                        |             |
| 20  | Atom Search Optimization                      | ASO          | 2019 | ✓                                        |             |
| 21  | Algorithm of the Innovative Gunner            | AIG          | 2019 | ✓                                        |             |
| 22  | Projectiles Optimization                      | PRO          | 2020 | ✓                                        |             |
| 23  | Gradient-Based Optimizer                      | GBO          | 2020 | ✓                                        |             |
| 24  | Dynamic Differential Annealed Optimization    | DDAO         | 2020 | ✓                                        |             |
| 25  | Lévy Flight Distribution                     | LFD          | 2020 | ✓                                        |             |
| 26  | Solar System Algorithm                        | SSA          | 2020 | ✓                                        |             |
| 27  | Archimedes Optimization Algorithm             | AOA          | 2021 | ✓                                        |             |
| 28  | Material Generation Algorithm                 | MGA          | 2021 | ✓                                        |             |
| 29  | Crystal Structure Algorithm                   | CryStAl      | 2021 | ✓                                        |             |
| 30  | Gamma Ray Interactions Based Optimization     | GRIBO        | 2021 | ✓                                        |             |

Moreover, the Figure 5 shows the combinatorial t-way adoption of physic-based techniques for optimization in the last two decades. It can be easily seen that majority of the algorithms are not adopted in combinatorial t-way optimization, even though the GSA [254], BHA [274], and SCA [295] was adopted between 2006 to 2010, 2011 to 2015, and 2016 to 2010 range respectively.
Based on the above analysis, the reader can see out of the thirty (30) algorithms developed, only three (3) are adopted in combinatorial t-way optimizations, whereas others are not.

VII. DISCUSSION

Despite the effectiveness of nature-inspired metaheuristics and their popularity, it is observed that there are still some challenging issues concerning combinatorial t-way optimization problem in adopting such algorithms for optimization. Meanwhile, it is not quite clear why they are not employed and under exactly what conditions. Even though, out of the one hundred and ten (110) algorithms reviewed in this paper, only fourteen (14) were adopted in combinatorial t-way optimization. In addition, we foresee that these challenges can slightly decrease the rate of using optimization method into the combinatorial t-way testing field.

Another interesting observation in this study is that all these nature-inspired metaheuristics have some dependent parameters settings, and their values can directly affect the performance of the algorithm for a better optimization. But it is not clear what the best values are for the parameters and that is the main reason for tuning these parameters to achieve a better optimization. However, the combinatorial t-way testing strategies have shown an imperative symbol of tuning parameters setting of an algorithm to obtain a better solution. Combinatorial t-way testing strategies such as Harmony Search Strategy (HSS) [177], Hybrid Artificial Bee Colony (HABC) strategy [317], Sine Cosine Algorithm for generating Variable t-way test suite Strategy (SCAVS) [299], PWiseHA strategy [181], and Combinatorial Testing Strategy using Jaya Algorithm (CTJ) [226], aim to use different number of parameters setting for the adopted algorithm and achieved good optimization.

Finally, all metaheuristics has a simple structure; thus, they can be easily adopted in different areas for becoming a more efficient in optimization solver. Even though, there are some related research on optimization problems that are yet to employ metaheuristics method such as Ref. [318] for minimizing integrated process planning and scheduling problem. Ref. [319] for traveling salesman problem in reducing the expected runtime of multi-objective evolutionary algorithms. Ref. [320] a robust support vector algorithm is employed to addressed a convex optimization problem. Ref. [321] improved linear kernel to address cycle contraction problem using kernelization algorithm. However, there is still another important issue which have not been addressed in combinatorial t-way testing known as privacy protection. An individual's or a group's ability to seclude themselves or information about themselves, and therefore express themselves selectively, is known as privacy [323], [324], [325]. The concept of responsible use and protection of information falls under the area of privacy, which is partially overlapped with security [325]. Private laws include the right not to be exposed to unapproved breaches of privacy by an individual or group [325], [326]. Traditional security measures such as identity verification and access control can prevent unwanted users from accessing data, but they can't stop internal cloud users from accessing and revealing sensitive information [327]. As such, there are some research focuses on this privacy issues within different domain such as digital library [328], [329], cloud computing [330], [327], e-commerce [331], and so on. Therefore, inclusion of privacy issue in combinatorial t-way testing strategy domain is what is more welcome.

Moreover, a suggestion of some future paths of investigation for researchers who are interested in the combinatorial t-way testing field is to employ more of these...
algorithms by tuning their parameters setting to achieve an optimal solution. This suggestion will upsurge the use of optimization method in combinatorial t-way testing.

VIII. CONCLUSION
In this paper, we provide an up-to-date review of current state of use of nature inspired metaheuristic algorithms and a suggestion for promising research opportunities around combinatorial t-way optimization is offered. It has been observed that the sources of inspiration for nature inspired metaheuristic algorithms development are very effective in solving various optimization problems. As such, the paper reviewed distinguished one hundred and ten (110) new outstanding metaheuristics between the years 2001 to 2021 based on their current state of use to inspire future research in the field of combinatorial t-way optimization. Moreover, we have briefly summarized all the algorithms into four (4) different classifications as evolution-based, swarm-based, human-based, and physic-based. Based on these classifications, we have focus more on the application of each metaheuristic in combinatorial t-way testing for optimization. However, it’s very important to note that although from the review in this paper and discussions above, it can be easily concluded that this nature inspired metaheuristic algorithms are quite young and majority were not even adopted around combinatorial t-way optimization which can to some extent reduce the rate of using optimization method into the area. Even though, some metaheuristics have been addressed in different optimization problem. Further, this research can also be a guided to include the young nature-inspired metaheuristic techniques with refining their intensification and diversification to fit in addressing combinatorial t-way optimization problem. Therefore, the review in this paper can be a comprehensive source of information to form a basis or starting point for further research.

FUTURE RESEARCH SUGGESTIONS
Adoption and application of these outstanding nature inspired metaheuristic algorithms into the combinatorial t-way optimization is the key part of this review paper. As such, the following interesting future research agenda are enumerated:

1. The like of or recently developed metaheuristics like TGA, SO, COA, TSA, BWOA, AVOA, RCM, SAR, TTA, LFD, SSA, AOA, MGA, and others that have not been adopted to be employed for solving combinatorial t-way optimization problem.

2. For instance, this paper reviewed the outstanding nature inspired metaheuristic algorithms to extract those adopted and not adopted in the t-way optimization problem. In future, similar work could be applied on other major areas of optimizations such as engineering problems, image segmentation problems, feature selection problem, and so on.

3. Also, to introduce a privacy issue in combinatorial t-way testing domain since almost all t-way strategies are available on a cloud database.

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