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Farmland fertility: A new metaheuristic algorithm for solving continuous optimization problems

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ABSTRACT

Nowadays, the use of metaheuristic algorithms has dramatically increased in order to achieve the optimal solution in solving continuous optimization problems. In this paper, a new metaheuristic algorithm that is inspired by farmland fertility in nature is presented; this algorithm divides into several parts of the farmland, and to optimize solutions of each section with optimal efficiency of two types in internal and external memory. In order to evaluate the farmland fertility, we simulated it on 20 main function of mathematical optimization that is important to evaluate this type of algorithms and the results displayed. This farmland fertility has been compared with other metaheuristic algorithms such as; artificial bee colony (ABC), firefly algorithm (FA), harmony search (HS), particle swarm optimization (PSO), differential evolution (DE), bat algorithm (BA), and improved PSO and the results are displayed clearly. Simulations show that the farmland fertility often acts better than other metaheuristic algorithms. The farmland fertility in problems with smaller dimensions problems has been able to act as a strong metaheuristic algorithm and it has optimized problems nicely. Furthermore, the farmland fertility in problems with larger dimensions has been able to perform better than other algorithms. The effectiveness of other algorithms decreases significantly with number of dimensions and the farmland fertility obtains better results than other algorithms.

1. Introduction

In recent years, the use of metaheuristic algorithms has surprisingly increased for solving various problems of search and discrete and continuous optimizations. Metaheuristic algorithms are the suitable solution for continuous optimization problems due to an increase in complexity of continuous optimization problems and disability of mathematical methods in providing optimal solutions. Mathematical procedures have been used in solving many scientific and engineering problems and they cover a very wide range of different issues. However, mathematical procedures are still facing great difficulties in solving optimization problems despite the exact efficiency. In recent years, efforts and researches conducted by researchers have led to invent algorithms inspired by natural phenomena. A phenomenon that investigated the evolution and behavior of nature's creatures, which has led to presentation of metaheuristic algorithms [1–8], along with algorithms derived from nature, other evolutionary metaheuristic algorithms were invented for optimization problems [9–11]. So far, numerous invented metaheuristic algorithms have been inspired by the nature. Furthermore, we could mention most important algorithm in the name of PSO [12]. It is an algorithm based on population. In this algorithm, the numbers of particles constitute a swarm (population) and in fact, particles are considered solutions of a function or problem. The population of particles moves in space of a problem, and tries to find the optimal solution in the search space based on their individual experiences and collective experiences. PSO is an optimization algorithm, which provides a population-based search that each particle in it changes its position within time. ABC [13] is one of the metaheuristic optimization algorithms that have been inspired by exploratory behavior of a ABC for solving continuous optimization problems with large spaces. This algorithm begins to work with the creation of the initial population of random vectors and in any repetition of the algorithm, ABC finds new answers by doing random searches around obtained answers in previous repetition.

Original idea of FA [7] inspired by optical communication among FFs. This algorithm can be considered as manifestations of swarm intelligence, that in the original version of this algorithm, each member of a group of FFs moves toward the point that their own best personal experiences has occurred at that point. With regard to the existent defects in the original version of this algorithm, in

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its improved versions there have been proposed changes in movement strategy of FFs. BA [14] is based on echolocation behavior (sound reflection) in bats with different pulse rate of emission and loudness. Search reinforced by random walk algorithm. The choice of best case continues until we see one of the conditions the best stop and up to now, many hybrid and improved versions have been presented after the primary presentation of this algorithm [15–19]. Farmland fertility use of both internal memory and external memory, population-based algorithm is classified in the class of algorithms for memory usage. The proposed metaheuristic algorithm divides search space into several parts and according to information that acquires from the existent solutions in section and considered changes according to the steps of farmland fertility is applied on solutions of each section individually.

The rest of the paper is organized as follows. Section 2 describes the Global optimization. Previous work describes in Section 3. In Section 4, we introduced algorithm of farmland fertility. Section 4 contains the theory, flowchart, and formulation of the farmland fertility that in this section, six stages of the farmland fertility are shown step-by-step. In Section 5 is shown result and evaluation of the farmland fertility. We considered 20 functions of standard test, so we tested and investigated their efficiency and performance along with the farmland fertility using these functions and we recorded and showed the obtained results in separate figures. At the end of this paper, we presented general conclusion.

2. Global optimization

Global optimization seeks universal solution of a limited optimization model and it is extremely important in many applications; such as; image processing, antenna design, chemistry, wireless sensor network, and so on. Solution methods of optimization problems are not easy and they are complex and difficult because of their nonlinearity and having multiple local optima. Furthermore, global optimization is one branch of practical mathematics and created by functions according to certain standards.

Traditional methods such as; the gradient-based methods usually try to solve problems. In recent years, researchers have obtained many successes in this field. Furthermore, they have presented some new optimization algorithms to solve these problems [20–24]. Optimization has important role in sciences, engineering, etc. Solving problems related to optimization is a critical issue. The best option for the convex, or at least uni-modal, optimization problems are local optimization methods. A local method may not be suitable for real-world problems that are not convex. It is impossible to demonstrate a local optimum is global. A meticulous global optimization algorithm needs to the search space. In addition to that, by increasing the dimensions of the search space, computational time for exploration will be long, too. In global optimization problem, point x is in a subset $\Omega \subseteq \Phi$ where a certain function $f: \Phi \rightarrow R$, In these field, Ω, Φ, and f are called the applied region, the solution space, and the objective function, respectively [23]. Optimal amount for the objective function ($f^* \in \mathbb{R}$), the minimization problem described by Equation (1):

$$\min(f : \Phi \rightarrow \mathbb{R}) = \mathrm{x} \in \Omega \subseteq \Phi | \forall \mathrm{y} \in \Omega)(\mathrm{f(x)} \leq \mathrm{f(y)}) \quad (1)$$

Analytic methods and numeric methods are largely used for solving problems. These methods are deterministic and stochastic. Stochastic global optimization algorithm is a repetitive algorithm that produces solutions using by stochastic operations. Stochastic optimization methods solve the more complex optimization problems and they are usually simple and easy to perform.

In Table 1, n is population's size, $P_t \in \Omega^n$ is equal to population at repetition $t \geq 0$, $NITPop : \mathbb{N} \rightarrow \Omega^n$ is as a function that creates the initial population, $NEXTPop : \Omega^n \rightarrow \Omega^n$ is called stochastic search, $END : \Omega^n \times \mathbb{N} \rightarrow Bool$ presents time of stopping the SGoal (n) process. $BEST : \Omega^n \rightarrow \Omega$ is a function that has been able to access best solution in the population according to the considerable optimization problem. See Eq. (2).

Table 1
Global Optimization Algorithm.

Algorithm 1. Stochastic Global Optimization Algorithm.

SGoal(n)
1 $t_0 = 0$
2 $P = INITPop(n)$
3 ***while*** $\rightharpoondown END(P_t, t)$ ***do***
4 $P_{t+1} = NEXTPop(P_t)$
5 $t = t + 1$
6 ***return*** $BEST(P_t)$

$$BEST(x) = x_i | \forall_{k=1}^{n} f(x_i) \leq f(x_k) \bigwedge f(x_i) < \forall_{k=1}^{i-1} f(x_k) \quad (2)$$

Optimization of physical systems is a very important process to regulate and control variables and it supplies optimum solution for physical/mechanical problems. Principle criteria in selecting an optimization algorithm are convergence speed and precision [20]. Optimization is a process of finding optimal values for the factors of a specific system from all the possible values, eventually, it maximize or minimize output [25,26]. In the last two decades, scientists and researchers have interested in developing stochastic optimization techniques. As a result, minimization of damages, costs and times, or maximization of advantages, profits and efficiency is original purposes of an optimization problem. Old deterministic methods or algorithms could not solve a large number of problems until, thus, researchers presented new algorithms that were inspired by the various natural processes.

3. Related works

Over the past two decades, metaheuristic algorithms have played an important role in solving and optimizing complex and difficult issues in various fields. These algorithms only need information about the target function and do not require other side features such as; differentiation or continuity, and are easy to understand and have good convergence properties. The metaheuristic algorithms have two major advantages. One of these advantages is good information sharing-mechanisms, which can promote an algorithm to accelerate convergence in specific circumstances, and the other advantage of it is their trap in local livestock, which is very low. Different categories exist for metaheuristic algorithms in the literature of these algorithms (based on group intelligence [27], evolution [28], physics-based [29], etc.), but more of these algorithms are metaheuristic optimization Inspired by the collective behavior of insects and animal groups in nature such as;; herds of animals, bats, hamster, colony of ants and birds and flying fruit. In the following section, previous works regarding ultra-innovative algorithms and their combination along with how to improve these algorithms are given.

The first and most popular evolutionary inspirational technique is the GA, which Holland simulated in Darwinian evolution in 1992. Another popular algorithm is PSO, first developed by Kennedy and Aarhart. The PSO algorithm inspired by the bird's social behavior and it uses several particles that fly in search space to find the best solution, and the accelerated version of this algorithm was introduced in [32]. Later, there are many metaheuristic algorithms for solving optimization problems, one of which algorithms is the ABC, a global crash-based and population-based optimization method and the behavior of honey colony exploration in nature in order to solve continuous optimization issues which is inspired by large spaces initially proposed by Karaboga and Basturk [34,33] in 2005. One of the problems of the standardized bee in standard algorithms is slow convergent, and this problem has resulted in improved versions of a combination of ABC algorithms by researchers. For example, in [35], a modified ABC algorithm this problem has been improved based on the best-generalized approach and a limited adaptive strategy for global optimization problems has been proposed. In [36], the cloning algorithm of synthetic bee has been suggested with recombination of the gene for optimizing the numerical function, and therefore, the gene recombination operator is applied in the ABC algorithm in order to accelerate the convergence and in an improved version of the other ABC algorithm. Adaptation is based on the best of the whole for general optimization is based on the best global nominee for global optimization [37]. Research shows that both PSO and ABC algorithms have better performance in many classes and numerical optimization problems [38–40]. Gam et.al. presented the HS algorithm in 2001 [41]. This algorithm follows the process of searching musicians for the best of harmony. HS algorithm have a many applications [42–45]. However, the HS algorithm has a low-convergence problem [46] and is sensitive to parameter adjustment and is easily trapped in the local trap [47]; therefore, many efforts have been made to increase the accuracy and convergence and efficiency of the HS algorithm [48–51], which was presented by Sarkhel et.al. in the latest research of the new HS algorithm embedded with oppositional education in 2017. The BA proposed by Xin-She Yang [51] which is also a collective intelligence-based algorithm based on the bat's reflection behavior at different pulse rates and loudness. Studies show that the BA can solve limited and unrestricted optimization problems with more efficiency and power than GA and PSO [53–55]. Despite the improvements, BA has been reported in some studies [56–58], whose performance may be diminished by increasing the dimensions of the problem, which has led to several types of bat altogether. In the latest improved BA presented by Asma Chakri et.al. [59]. A new BA for continuous optimization problems to overcome an unplanned convergence, due to poorly explored BA's ability under certain conditions, has been introduced to improve directional BA performance.

The FA is designed with a glow pattern of lightning sparkle glow properties [60]. In the FA, there are two important issues of light intensity variation and the formulation of the amount of charms or charm. In the FA, each firefly moves toward the luminous firefighter, and when there is no more lightning-fast firefighter, random motion is done. A random motion is a simple and weak operator that is used in the FA that sometimes catches the FA in a local trap [61]. DE [62] is one of the strongest randomization methods that utilize jump operators, intersection operators, and selection operators on any population generation to achieve optimal globalization. The use of these operators in the DE algorithm has made this algorithm suitable for improvement and combination with other metaheuristic algorithms, which in [61] presented a new luminosity algorithm for global optimization, which combines some of the advantages of the algorithm of the night Fluctuations and DE are a strong combination algorithm for solving optimization problems. Furthermore, in [63] a hybrid algorithm based on a FA and DE for global optimization has been developed that the proposed method is designed in this reference. It addresses the weaknesses of the FA using an evolution algorithm Tail covering. Researchers for a variety of issues have proposed many new metaheuristic algorithms over the past few years. The coexistence search algorithm is one of the newest methods for solving optimization problems based on the interactions of organisms in nature. This algorithm was first introduced in 2014. It was introduced by Cheng and Priego [64] and an improved version of this algorithm called the integrated confusion-search integration algorithm was introduced in 2017 [65]. The Krill Herd (KH) algorithm is a wildly inspired method provided by Gandomi in 2012 [66]. This algorithm is based on the nutritional value of krill, which is the shortest distance from each krill from the food and center of other krill gathering as a target function for krill moving. The krill group uses Lagrangian motion, which includes inductive motion, random propagation, and searcher movement. In the comparative version of the krill shuffler algorithm [67], by adding a randomization technique, the krill group algorithm has been strengthened by a powerful adaptive coupling to obtain a general optimal solution with fast convergence and low parameter dependence. Dugan and Olemm first proposed the vortex search algorithm in 2015 to solve continuous optimization problems, which is a non-demographic overclocking whose main idea used, is to use an adaptive approach to adjust the size of the search step around the response in each repetition of the algorithm [68]. In [69], he proposed an optimization algorithm for Wall, which emulates the new metaheuristic optimization algorithm called the Wall Algorithm for hovercraft social behavior, derived from the Bubble net hunting strategy. A new social spider (SS) algorithm is proposed for solving global optimization problems [70]. In terms of simplicity and implementation, SS algorithm is relatively simple and can solve a wide range of continuous optimization problems.

4. Farmland fertility

In this paper, we proposed new algorithm which is named farmland fertility, Therefore, farmers divide an environment of farmland into different sections in terms of soil quality; any section of farmland has soil with specific quality that soil quality is different in each section of farmland. Soil's quality of each section of farmlands changes by adding a series of special materials. In this paper, the purpose of a specific material is to contain all chemical fertilizers, organic fertilizers, animal-based fertilizers and green manure or any type of material that farmers use to improve the quality of farmland. As a result, materials have important effects on physical and chemical properties of soil. These materials help the soil in a portion of farmland to maintain more water in itself. Furthermore, soil quality increases, and produces better and more quality products with high efficiency. On the other hand, available nutrients in fertilizers help plants to obtain lush and green growth. Therefore, in this algorithm, the purpose of material is all fertilizers that farmers combine with their agricultural soil, to enhance soil quality that increases production and quality of products. These materials have properties that by adding to the soil in farmland improve or reduce soil quality. Thus, according to soil quality of each section in farmland, farmers try to use appropriate materials with same soil for its recovery. Farmers, who live around these parts of farmland, have information about number of sections of farmland and soil quality of each section. Therefore, farmers refer to this section of farmlands; they carry a series of special materials with farmland fertility themselves and add this material to the soil in farmland, so that they can change soil quality of each section of farmland. The significant point is that, farmers try to add material to the soil in farmland in each visit, to obtain better quality than previous quality of soil. Furthermore, in next times, when farmers decide to go to this farmland, because the amount of soil quality in each section of farmland is clear, finally, they can decide about amount and type of materials that should carry to enhance soil quality in each section of farmland. Eventually, they change soil quality of the different sections of farmland.

In, framers exert necessary changes in soil of any part of farmland after visiting farmland and they note soil quality of each section of farmland and use these notes and information in the various sectors of farmland. Therefore, after next observation, they can decide better about improvement of soil quality in each sec-

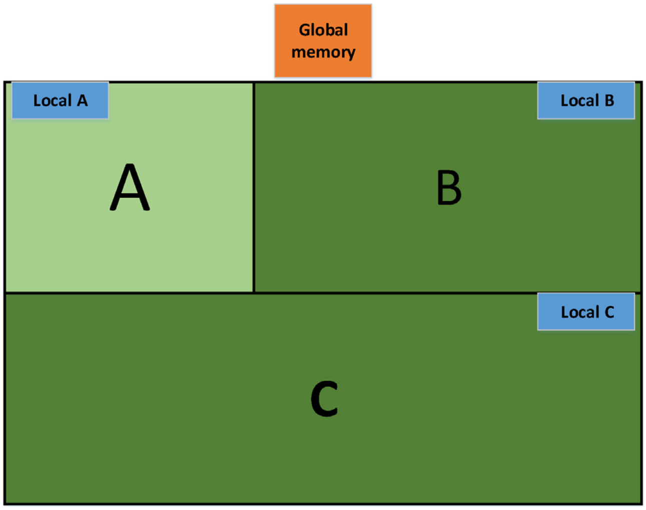

Fig. 1. Partitioned Example of Farmland and Local Memory and Global Memory.

tion. After determining soil quality of each section in farmland, for each section of farmland that has the worst quality, they considered the greatest amount and highest quality of special materials to change soil quality in that part. Thus, worst part of farmland will have greatest percentage of changes, and other parts of farmland need distinctive percentage of special materials to change their quality. Furthermore, there is a series of storage or memory units next to each parts of farmland. These memories record best quality for soil that farmers have obtained by adding materials until now that in this algorithm is called memory of each section or local memory. A series of storage devices (warehouses) is considered to keep the best quality of available soil in all sections of the farmland that calls total memory or global memory. Considerable point in the case of these two memories is that local memory saves only the best solutions of previous visits of each section individually. While the global memory saves the best solutions that finds so far in all visits for all sections. Generally, local memory saves the best solutions that ever found in each of the sections and global memory saves best solutions that ever found in all space searches (Fig. 1). As you can see in Fig. 1, for example, farmland is divided into 3 sections, each section has its own local memory and a global memory, and part A has soil with lowest quality.

Farmers use both of these memories for next visits. In future visits, farmers try to add material and then combine it with one of the bests in the global memory or one of the bests in the local memory, so that they can produce soil with higher quality. In this algorithm, part of the farmland that has the worst quality, is combined with existing solutions in global memory and existing solutions in other parts of the farmland is combined with all available solutions in the search space, so that it can present better results. Each of the agricultural sections changes its solution with global memory and random solutions in the search space and then farmers decide to combine any of the existing soils in each section of farmland based on best of the best in their local memory. Of course, there is a bet about combination with the best cases in local memory, which means that not all solutions are combined with their local memory and at this stage; some of solutions are combined with best global solution to improve quality of existing solutions in them. There is a point about these materials: These materials are different themselves. In fact, farmers to change soil quality of farmland by carrying different materials. They can test types of these materials on soil in farmland. Therefore, farmers try to add materials to soils within each section that leads to improve soil quality. Furthermore, farmers know according to previous experiences that what kind of materials have had more influence on soil quality of farmland. In order to obtain better results, at the time of visit, they use materials that have ever had better results to change soil quality of farmland that have the worst quality, these materials can produce soils with better quality and finally, farmers use random materials to change soil quality of other sections

After we introduced algorithm of farmland fertility, we want to explain stages of this algorithm with formulas and the key points step-by-step. This algorithm is generally composed of six stages that flowchart of Fig. 2 shows the farmland fertility and stages of algorithm based on the flowchart and key points is completely shown in 6 steps.

4.1. First stage: initial values

In all metaheuristic algorithms, the first stage comprises production of answers and solutions based on the issue. Furthermore, the farmland fertility should produce all considerable solutions in the first step. At this stage, production of the population is according to the number of sections of farmland and the number of available solutions in each section. In the form of Eq. (3) is expressed the number of initial population:

$$N = k * n \tag{3}$$

In Eq. (3) N represents the total number of population in the search space. k determines the number of parts for optimization problem. Standard number of sections of the farmland can be determined According to the optimization problem. As a result, the whole search space is divided into (k) sections that each section has a specific number of solutions n represents the number of existing solutions in each section of farmland. This number is variable and an integer number. In fact, it is number of available solutions in each part of search space. For random production of search space, we can use the Eq. (4):

$$x_{ij} = L_j + rand(0,1) \times (U_j - L_j) \tag{4}$$

In Eq. (4), Uj and Lj are top and bottom bounds of variable x, respectively. rand is function of random numbers is in the range of (0,1) that j=[1. . ..D] represents dimension x and i is equal to[1. . ..N]. At this stage, available solutions in the whole search space are evaluated according to the objective function and kinds of standard functions are standard functions of optimization in this paper, which are listed in Section 2.3. Without regard to number of sections of farmland, this stage is done over the all of existing solutions in the entire search space. Thus, amount of suitability and fitness of each solution is determined in search space.

4.1.1. Determine K value

In this paper, the main problem is the k variable that distinguishes the proposed algorithm from other metaheuristic algorithms. k is considered for partition of search space (As farmers divide their land into different parts). In the real world, farmers separate their lands from other lands in rectangular or square shapes according to Fig. 1. However, in the search space of metaheuristic algorithms is not possible. Because it is possible to divide the search space into an infinite number of rectangular or square shapes, and this subject is a NP Hard problem. Nevertheless, if we want to divide the search space into a rectangular, square or circular form in the metaheuristic algorithm, it must be in accordance with the principle of randomness of metaheuristic algorithm. As a result, the most appropriate way to divide search space in metaheuristic algorithms is to divide the search space randomly. Hence, in the proposed algorithm for random partition of the search space, a solution is provided according to Fig. 3.

In all metaheuristic algorithms, firstly solutions are randomly created such as Fig. 3a. In Fig. 3b, by preserving the principle of ran-

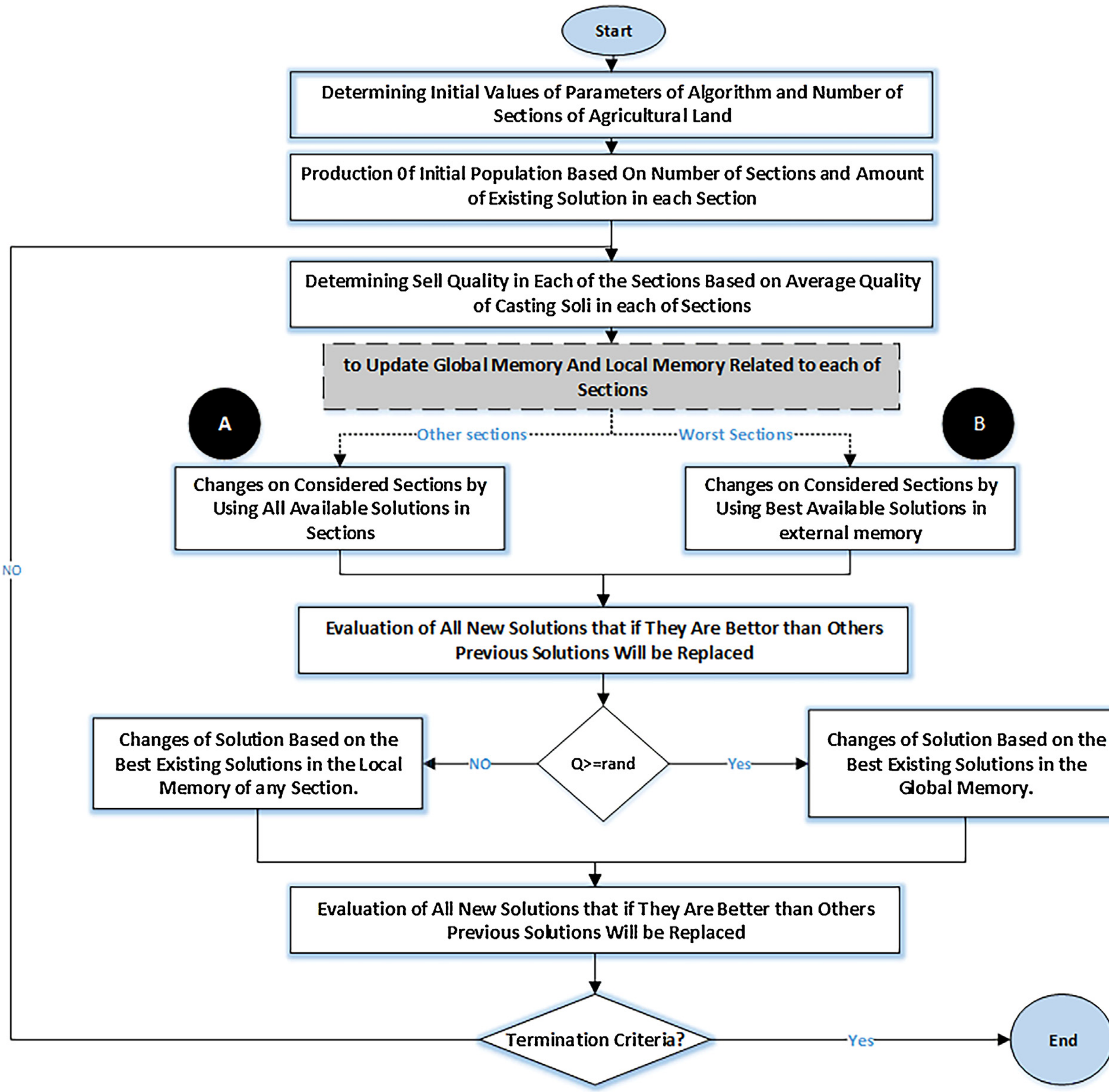

Fig. 2. Flowchart of Farmland Fertility.

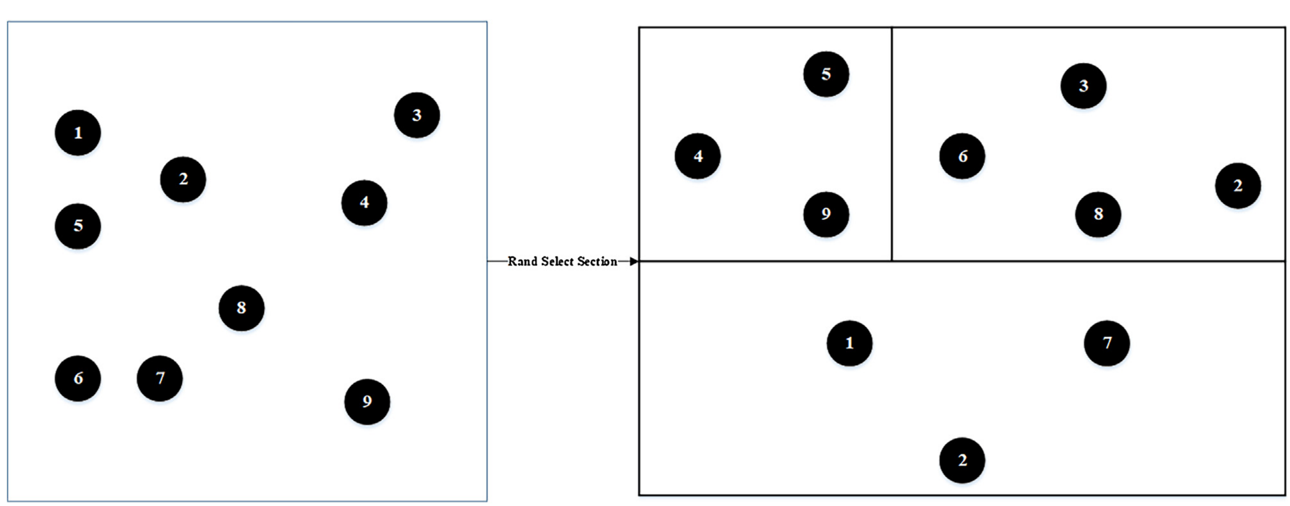

Fig. 3. Partition the Search Space in the Proposed Algorithm.

domness of metaheuristic algorithms, each solution is randomly assigned to one of the sections. In this paper, we used random method of assigning solutions to different sectors to divide search space into k-section in the rectangular or square forms. Another major issue is the value of k, (so that we can divide the search space into exactly several sections) that can be considered as an optimization problem. In here, we will show that value of k can be a limited or constant value, by presenting several assumptions and doing different experiments and displaying the results of Tables 4 and 5.

First Assumption: if k = 1 (the lowest possible value), in this case, according to the flowchart, the proposed algorithm (Fig. 2) will be executed according to one of the specified steps A and B. If Step A is executed, changes take places on all the desired solutions using the available solutions in search space. As a result of this, it causes the algorithm to be very high exploration and very low productivity (late convergence); and if stage B is executed, changes is applied to all the desired solutions using the best available solutions, and thus, it results in very low exploration and high productivity of the algorithm (early convergence). Therefore, the k = 1 causes an imbalance between the exploration and the efficiency of the algorithm.

Second Assumption: If k = Npop (the maximum possible value), in this case, each solution is considered as a part, practically, the internal memory does not mean in this algorithm, and according to the flowchart of the proposed algorithm (Fig. 3) will be executed the step A and, and so the algorithm converges too late.

Third Assumption: If k = 2 (rather small value), in the first and second assumptions, it was proved that the value of k cannot be equal to 1 or maximum possible value. Therefore, according to the first assumption, we proved that k> = 2, and according to Fig. 3, steps A and B must be run at least once, half of the solutions are optimized globally, and half of the solutions will change randomly (by using existing solutions in the entire search space). This kind of partitioning can be somewhat good because both exploration and productivity are created in the algorithm. In description to that, Tables 4 and 5 show that sometimes the value of 2 can work well and it can be one of the options that works better when the initial population is low. However, weakness of this case is important, so that, we need less exploration and more productivity, at the end of the repetition of metaheuristic algorithms. While, k given the value of 2, we will apply exploration on half the population until the end of the algorithm.

Fourth Assumption: If k = 8 (a relatively large value), in the third assumption, we proved that the k value is equal to 2 and it maintains the exploration in a way. Sometimes, this work causes the algorithm to not obtain (to lose) the optimal answer. In this assumption, if the value of k is equal to 8, this means that most solutions are best solutions for global memory, and so we will probably use the best solutions of local memory and the algorithm performs highly early convergence. In description to that, Tables 4 and 5 show that with k = 8, the algorithm works more poorly and it shows bad results than other values. As a result, if the k is greater than 8, then the algorithm will be weaker.

Fifth Assumption: If k = x (fit value), It was proved in the third and fourth assumptions, if k is equal to 2 and 8, problems will occur for the algorithm and its convergence method. Therefore, according to all assumptions and the results obtained in Tables 4 and 5, the value of k is equal to $2 \le k \le 8$ and range of its numbers is specific. Suppose that, if k = 4, this means that we will use best solutions of global memory and then, it is possible to use best solutions of local memory. As you can see in Tables 4 and 5, in most implementations, (k = 4) value of k can maintain the balance between exploration and productivity and stick much less at the local minimum.

As a result of this, all metaheuristic algorithms try to balance between exploration and productivity, in the proposed algorithm, we also tried to maintain the balance between exploration and productivity by using the two variables k and Q. The main part of the proposed algorithm is to divide the search space into k section, hence, the determination of k-value can be sensitive that in this section, we proved by 5 assumptions, which k-value can be $2 \le k \le 8$. Based on the results obtained from Tables 4 and 5, and analysing and proving 5 assumptions, our further emphasis is on values 2 and 4. However, there are NP Hard optimization problems in the real world, and we can consider the value of $2 \le k \le 8$ to solve them. In addition, the proposed algorithm will certainly be able to solve all optimization problems well and properly.

4.2. Second stage: determining soil quality in each part of farmland

After determining the total number of initial population according to Eq. (3), generating the initial population by Eq. (4) and fitness of all of existing solutions in the search space and after determining fitness of solutions, we obtained determining the quality of each of the sections of farmland (Sections of the search space) by Eq. (5) and Eq. (6). The quality of each section of farmland obtains by average of existing solutions in each section of farmland.

$$Section_s = x(aj)\,,\ \mathrm{a} = \mathrm{n}^*(\mathrm{s}-1) : n * s\, s = \left\{1, 2, \ldots .k\right\}, \quad j = \left\{1, 2, \ldots .4\right\} \tag{5}$$

Eq. (5) separates available solutions in each section, simply. So that, we can calculate average of each separately. According to Eq. (5), x is equal to all of solutions in the search space and s represents number of section and j=[1. . ..D] shows dimension of variable x.

$$Fit\_Section_s = Mean\left(\text{all Fit}\left(x_{ji}\right) in\, Section_s\right)\ .s = \left\{1.2.\ldots .k\right\}. \quad i = \left\{1.2.\ldots .n\right\} \tag{6}$$

In Eq. (6), *Fit_Section* defines quality of solutions for each section of farmland that each section has a special amount of quality and in the search space is the average fitness or suitability all of available solutions in each section. Hence, for each of the sections of farmland, is achieved total average of the solutions within any section and finally, it is saved in $Fit\_Section_s$. At this stage of the farmland fertility is determined each of sections and their solutions and the average of each section.

4.3. Third stage: update memories

After determining solutions of each section of farmland and the average of each section, we update local memory of each of the sections and global memory. Some of best cases of each section are stored in the local memory and best cases of all sections are stored in global memory that is determined by the number of best local memory according to Eq. (7) and the number of best global memory according to Eq. (8).

$$M_{local} = round\left(\mathrm{t} * n\right) \quad 0.1 < t < 1 \tag{7}$$

$$M_{Global} = round\left(\mathrm{t} * N\right) \quad 0.1 < t < 1 \tag{8}$$

In Eqs. (7), (8), M_{Global} shows the number of solutions in global memory and M_{local} shows the number of solutions in local memory and solutions are placed based on the fitness and suitability in these memories and at this stage are updated both memory. After updating memories, the worst and the best parts are determined and algorithm enters the next stage.

4.4. Fourth stage: changing soil quality in each part of farmland

At this stage, after determining quality of each of sections by Eq. (6), section that has the worst quality, will have greatest changes.

Table 2
Classical Benchmark Functions (F01-F20).

No	Function Name	Formula	Bounds
F01	Sphere	$\sum_{i=1}^{d} x_i^2$	$[-100.100]^d$
F02	Sum of different powers	$\sum_{i=1}^{d} \lvert x_i \rvert^{i+1}$	$[-100.100]^d$
F03	Rotated hyper-ellipsoid	$\sum_{i=1}^{d}\sum_{i=1}^{i} x_i^2$	$[-65.65]^d$
F04	Griewank	$\sum_{i=1}^{d} \frac{x_i^2}{4000} - \prod_{i=1}^{d}\left(\frac{x_i}{\sqrt{i}}\right)$	$[-600.600]^d$
F05	Rastrigin	$10d + \sum_{i=1}^{d} x_i^2 - 10\cos(2\pi x_i)$	$[-5.12.5.12]^d$
F06	Levy	$sin^2(\pi w_1) + \sum_{i=1}^{d+1} (w_i - 1)^2\left[1 + 10sin^2(\pi w_1 + 1)\right] +$ $(w_d - 1)^2\left[1 + 10sin^2(\pi w_d)\right]$ Where $w_i = 1 + (x_i - 1)/4$	$[-5.12.5.12]^d$
F07	Ackley	$20exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(2\pi x_i)\right) + 20 + \exp(1)$	$[-32.32]^d$
F08	Schwefel	$418.9829 - \sum_{i=1}^{d} x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	$[-500.500]^d$
F09	Rosenbrock	$\sum_{i=1}^{d-1}\left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)\right]$	$[-10.10]^d$
F10	Zakharov	$\sum_{i=1}^{d} x_i^2 + \left(\sum_{i=1}^{d} 0.5ix_i\right)^2 + 0.5ix_i)^4$	$[-5.10]^d$
F11	Dixon-price	$(x_i - 1)^2 + \sum_{i=2}^{d} 2x_i^2 - x_{i-1})^2$	$[-10.10]^d$
F12	Michalewicz	$-\sum_{i=1}^{d} \sin(x_i)sin^{20}\left(\frac{ix_i^2}{\pi}\right)$	$[0.\pi]^d$
F13	Powell	$\sum_{i=2}^{d/4}[(x_{4i-3} + 10x_{4i-2})^2 + 5(x_{4i-1} - x_{4i})^2 + (x_{4i-2} - 2x_{4i-2})^4 + 10\left(x_{4i-3} + x_{4i})4\right]$	$[-10.10]^d$
F14	Alpine	$\sum_{i=1}^{d}\left\lvert x_i \sin(x_i) + 0.1x_i\right\rvert$	$[-10.10]^d$
F15	Styblinski-Tang	$0.5\sum_{i=1}^{d}(x_i^4 - 16x_i^2 + 5x_i) + 39.16599d$	$[-100.100]^d$
F16	Bent cigar	$x_i^2 + 10^6\sum_{i=1}^{d} x^2$	$[-10.10]^d$
F17	MATYAS	$0.26\left(x_1^2 + x_2^2\right) - 0.48x_1x_2$	$[-10.10]^d$
F18	BEALE	$f(x) = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$	$[-4.5.4.5]^d$
F19	CAMEL	$f(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	$[-5.5]^d$
F20	BOHACHEVSKY	$f(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1 + 4\pi x_2) + 0.3$	$[-100.100]^d$

The number of solutions of each section by Eq. (5) was determined. There is matter about the worst part of farmland in terms of quality and this is that all existing solutions in worst section of farmland are combined with one of the available solutions in the global memory according to Eqs. (9) and (10).

$$h = \alpha * rand(-1.1) \tag{9}$$

$$Xnew = h * \left(X_{ij} - X_{MGlobal}\right) + X_{ij} \tag{10}$$

In Eq. (10), $X_{MGlobal}$ is a random solution among existing solutions in the global memory and α is a number between zero (0) and one (1) that should be valued at the beginning of the farmland fertility. X_{ij} is a solution in worst part of farmland that is selected to apply changes and h is a decimal number that according to Eq.(9) can be calculated. As a result, *Xnew* as a new solution is obtained by applied changes. After making the changes on worst part of farmland, other sections should be combined with available solutions in the entire search space. Available solutions in other sections are determined by Eqs. (11) and (12).

$$h = \beta * rand(0.1) \quad (11)$$

$$Xnew = h * \left(X_{ij} - X_{uj}\right) + X_{ij} \quad (12)$$

In Eqs. (11), (12), X_{uj} is a random solution among existing solutions in the entire search space. This means that, between all solutions in sections is selected a random solution and β is a number between zero (0) and one (1) that should be valued at the beginning of the farmland fertility. X_{ij} is a solution relating to sections (Apart from the worst section) that is selected to apply changes and h is a decimal number that can be calculated according to Eq. (11). As a result, *Xnew* as a new solution, is obtained by applied changes.

4.5. Fifth stage: soil's combination

At this stage, as we expressed algorithm theoretically in Section (1), farmers decide to combine each soil within the sections of farmland based on the best available cases in their local memory ($Best_{Local}$) at the last stage. And so, there is a provision about the combination with the best in local memory. So that, not all available solutions are combined with local memory in all sections and at this stage, some of the available solutions in the all places are combined with the best solution ever found ($Best_{Global}$) to improve quality of existing solutions in the each section. The combination of considered solution with $Best_{Global}$ or $Best_{Local}$ is determined by Eq. (13).

$$H = \begin{cases} X_{new} = X_{ij} + \omega_1 * \left(X_{ij} - Best_{Global}(\mathrm{b})\right) & .Q > rand \\ X_{new} = X_{ij} + rand(0.1) * \left(X_{ij} - Best_{Local}(\mathrm{b})\right) & .\,else \end{cases} \quad (13)$$

In the Eq. (13), two methods may create new solution. In this equation, Q is a parameter between zero (0) and one (1) that must be determined in the beginning of the algorithm. This parameter determines amount of combination of solutions with best global ($Best_{Global}$). ω_1 as a parameter of the farmland fertility and it is an integer and should be determined at the beginning of the algorithm that its amount gradually decreases according to repetition of algorithm (Eq. (14)). X_{ij} is a solution that to apply the changes is selected from all sections. Consequently, *Xnew* is a new solution and it is achieved according to the applied changes.

$$\omega_1 = \omega_1 * R_v \,.\, 0 < R_v < 1 \quad (14)$$

4.6. Sixth stage: final conditions

At this stage, according to the objective function are evaluated the existing solutions in entire search space. In this paper, the kinds of objective functions are standard functions of optimization that we have mentioned in Table 2. Regardless of the number of sections, this stage is accomplished on all available solutions in the search space. Thus, the amount of suitability and the fitness of each of the existing solutions is determined in the search space. At the end of the farmland fertility, are investigated final conditions. If we confirm final condition, the algorithm ends. Otherwise, the algorithm will continue its work to establish final conditions.

5. Evaluation and experimental results

5.1. Standard test functions

We used 20 standard optimization functions for efficiency and performance of farmland fertility algorithm. They have been tested and investigated in the separate diagrams, and recorded and shown the obtained results. List of test functions used in proposed procedure with their mathematical model are shown in Table 2. It should be mentioned that the test functions introduced in this section are used for minimization problems [19].

Table 3
Valuation of Parameters of the Farmland Fertility and other Algorithms.

HS [10]	DE [71]	ABC [13]	FA [7]	Farmland Fertility
N=50	N=50	N=50	N=50	**N=50(K=2,N=25)**
HMCR=0.8	C=0.9	Nonlooker=50	$\alpha = .2$	$\boldsymbol{\alpha} = 0.6$
PAR=0.3	F=0.5	$\alpha = 0.1$	$\beta 0 = 1$	$\boldsymbol{\beta} = 0.4$
Hms=50	-	L=N*D*.6	$\gamma = 1$	**W=1,Q=.7**
D=[2,4,8,16]	D=[2,4,8,16]	D=[2,4,8,16]	D=[2,4,8,16]	**D=[2,4,8,16]**

5.2. Evaluation of the farmland fertility

We introduced 20 standard test functions in Section (3-1) and we showed mathematical models for each of the functions. After determining the initial parameters for the farmland fertility and other algorithms, we showed their initial values in Table 3. All algorithms in this table are the basic (fundamental) versions of algorithms.

At first, this section to evaluate the farmland fertility and the effect of k and n values on the standard functions is simulated and performed that are presented in Table 2. The results of this implementation are shown in Tables 4 and 5 on the different values of the parameters.

The results of Tables 4 and 5 show that the farmland fertility has been able to minimize amount of the objective function (it is one of the 20 objective functions that are presented in Table 2 in different circumstances. Furthermore, we can conclude that amounts of n and k must be considered according to objective function and the number of population, because with excessive increase of k will be worse obtained results and if the value of k is less than standard rate, again, we will see the worse results.

We have done several experiments to confirm the validity of efficiency of the farmland fertility that we can summarize into three comparative tests. The first experiment is related to the parameters of farmland fertility that in term of statistical tests such as; the average, best, and worst have shown in Tables 4 and 5. The second test is a comparison between the new farmland fertility and standard algorithms such as; the silkworm algorithm, HS algorithm, the DA on the 20 standard benchmark functions that the results shown in Figs. 4–10. For the third test, we compared results of the farmland fertility with the result obtained by [72 and 59]. For this work, we compared GA, the BA, PSO, and improved PSO with the results obtained from works [72] and [59] to simulate different benchmarks and functions, separately and we have shown in Tables 6 and 8, respectively. This section comprises experiment; second survey of the farmland fertility and comparison of standard algorithms such as; the silkworm algorithm, HS algorithm, the difference algorithm on the 20 standard benchmark functions. Functions 1 to 16 (F01-F16) are part of multi-dimensional functions that can be applied the desired dimensions for them and the results can be shown. However, F17-F20 are part of two-dimensional functions. Therefore, we considered Two-dimensional (2D) form for functions 17 to 20 and we showed in Fig. 4. On the other hand, functions 1 to 16 are multi-dimensional. We considered the number of dimensions of 4, 8, and 16 respectively; to assess them and showed results on these functions in Figs. 5–10.

The results of the implementation of the Farmland Fertility on 20-presented functions are shown in Table 2 and in Figs. 4–10 in the dimensions of 4, 8, and 16. As you see, in these results, we examined the farmland fertility in different dimensions and compared them with other algorithms, and for testing of change in the parameters k and n of farmland fertility in Tables 4 and 5, we considered types of different values for the farmland fertility. The results show that

Table 4
Assessment of the Farmland Fertility and Effect of K And N Values in Different Modes on Functions F01-F10.

Function	N	K	n	d	maxit	Best	Worst	Mean
F01	1000	2	500	4	20	3.1356E-07	1.2548E+03	5.7314
	1000	4	250	4	20	**7.254E-08**	5.95E+02	**1.2345**
	1000	5	200	4	20	1.754E-06	7.84E+02	1.9725
	1000	10	100	4	20	2.1561E-05	**1.4548E+03**	4.3589
F02	600	2	300	8	30	4.5410E-03	4.9763E+03	**1.876E+01**
	600	3	200	8	30	**1.1515E-05**	1.3324E+03	4.941E+01
	600	4	150	8	30	8.0183E-05	1.0093E+03	2.1045E+01
	600	6	100	8	30	2.3904E-03	**6.9763E+03**	3.5901E+01
F03	400	2	200	16	100	2.7002E-01	**3.199E-01**	9.897E-1
	400	4	100	16	100	2.0681E-02	1.688E-01	5.381E-2
	400	8	50	16	100	**1.0537E-03**	9.381E-02	**1.381E-2**
F04	240	2	120	32	200	21.572E+01	**28.2749E+01**	23.2749E+01
	240	3	80	32	200	11.178E+01	13.809E+01	12.340E+01
	240	6	40	32	200	**10.162E+01**	11.098E+01	**10.568E+01**
F05	100	2	50	10	50	7.70281E+01	**20.16798E+01**	13.072E+01
	100	4	25	10	50	**1.6135E+01**	12.5710E+01	**3.9496E+01**
	100	5	20	10	50	6.0132E+01	18.1628E+01	10.6105E+01
F06	800	2	400	10	20	3.97912E+01	**1.7923E+05**	2.3570E+03
	800	4	200	10	20	**0.56331E+01**	1.5472E+05	**2.1312E+03**
	800	8	100	10	20	2.9894E+01	1.4092E+05	2.188E+03
F07	400	2	200	20	50	8.3057E-06	1.99668E+01	**5.30340E-01**
	400	4	100	20	50	**5.1982E-06**	1.99321E+01	6.74212E-01
	400	8	50	20	50	7.7323e-05	**2.19785E+01**	6.10345E-01
F08	480	2	240	16	80	**1.0904E-3**	**1.15453e+03**	1.903880E+02
	480	3	160	16	80	5.0911e-05	9.764892E+2	**1.547737E+02**
	200	4	120	16	80	0.23016E+1	1.0112e+03	2.146871E+02
F09	1000	2	500	4	20	1.3481e-01	2.6538e+03	1.5555E+01
	1000	4	250	4	20	2.6381E-02	**4.7139e+03**	**7.9132E+00**
	1000	5	200	4	20	**1.1435E-02**	3.1848e+03	9.8081E+00
	1000	10	100	4	20	2.8498E-01	2.0049e+03	1.28513E+01
F10	600	2	300	8	30	**1.4268E-03**	3.9900E+00	6.49E-02
	600	3	200	8	30	8.5378E-03	2.68030E+01	1.432E-01
	600	4	150	8	30	4.0723E-03	1.04986E+01	**8.641E-02**
	600	6	100	8	30	6.5957E-03	**8.3252E+00**	1.708E-01

Table 5
Assessment of the Farmland Fertility and Effect of k and n Values in Different Modes on Functions F11-F20.

Function	N	K	n	d	maxit	Best	Worst	Mean Cost
F11	400	2	200	16	100	1.8141E+00	**1.9729E+00**	1.8891E+00
	400	4	100	16	100	**6.6835E-01**	1.4306E+00	**8.096E-01**
	400	8	50	16	100	7.0266E-01	1.0745E+00	8.422E-01
F12	240	2	120	32	200	−2.2574E-01	−8.5448E+00	−1.80938E-01
	240	3	80	32	200	−22.9668	−8.1148 E+00	−**1.72762E-01**
	240	6	40	32	200	−**20.7767**	−**8.6776 E+00**	−1.85908 E-01
F13	100	2	50	10	50	2.9774E-01	4.435 E-01	3.412E-01
	100	4	25	10	50	**5.6593E-02**	1.756 E-01	6.142E-01
	100	5	20	10	50	4.3224-02	**9.724 E-01**	**1.321E-01**
F14	800	2	400	10	20	1.9047E-01	1.37596E+01	1.2774E+00
	800	4	200	10	20	**1.6481E-01**	**2.11444**E+01	**1.1305**E+00
	800	8	100	10	20	2.9194E-01	1.46881E+01	1.9166E+00
F15	400	2	200	20	50	2.14761E+02	**6.9736e+03**	6.22404E+02
	400	4	100	20	50	**1.07329E+02**	5.6721e+03	**3.60653E+02**
	400	8	50	20	50	1.69994E+02	5.5008e+03	1.0145e+03
F16	480	2	240	16	80	5.168877+02	**2.6764e+03**	8.843521E+02
	480	3	160	16	80	2.389117+02	1.7325e+03	4.265275E+02
	480	4	120	16	80	**1.386145+02**	9.9454E+02	**2.861308E+02**
F17	100	2	50	2	30	1.1342e-10	**1.0848E-4**	8.7680e-05
	100	4	25	2	30	1.4668e-10	5.2944E-3	1.60558E-06
	100	5	20	2	30	**3.5875e-10**	9.62112E-3	**2.13458E-04**
F18	60	2	30	2	40	2.2284e-08	**2.5944E-2**	**3.317212E-4**
	60	3	20	2	40	7.8847e-12	2.4487e-03	4.376366E-08
	60	4	15	2	40	**7.4562e-13**	2.7542E-04	**2.861308E+08**
F19	48	2	24	2	100	4.9502e-21	**5.0521e-21**	4.9533e-21
	48	3	16	2	100	1.3179e-27	5.1146e-25	1.2604e-26
	48	4	12	2	100	**2.3911e-18**	2.3923e-18	**2.3912e-18**
F20	80	2	40	2	40	6.1839e-14	**3.3765e-09**	5.4460e-11
	80	4	20	2	40	4.3521e-13	1.4244e-08	1.9923e-10
	80	8	10	2	40	**1.6593e-12**	4.4167e-09	**1.5110e-10**

the farmland fertility is superior to other metaheuristic algorithms in most various situations of dimensions in optimizing functions. Furthermore, we can see farmland fertility in the high dimensions of functions has been able to do better than other metaheuristic algorithms such as; HS algorithm, difference algorithm, FA, and ABC. There is a significant difference between the farmland fer-

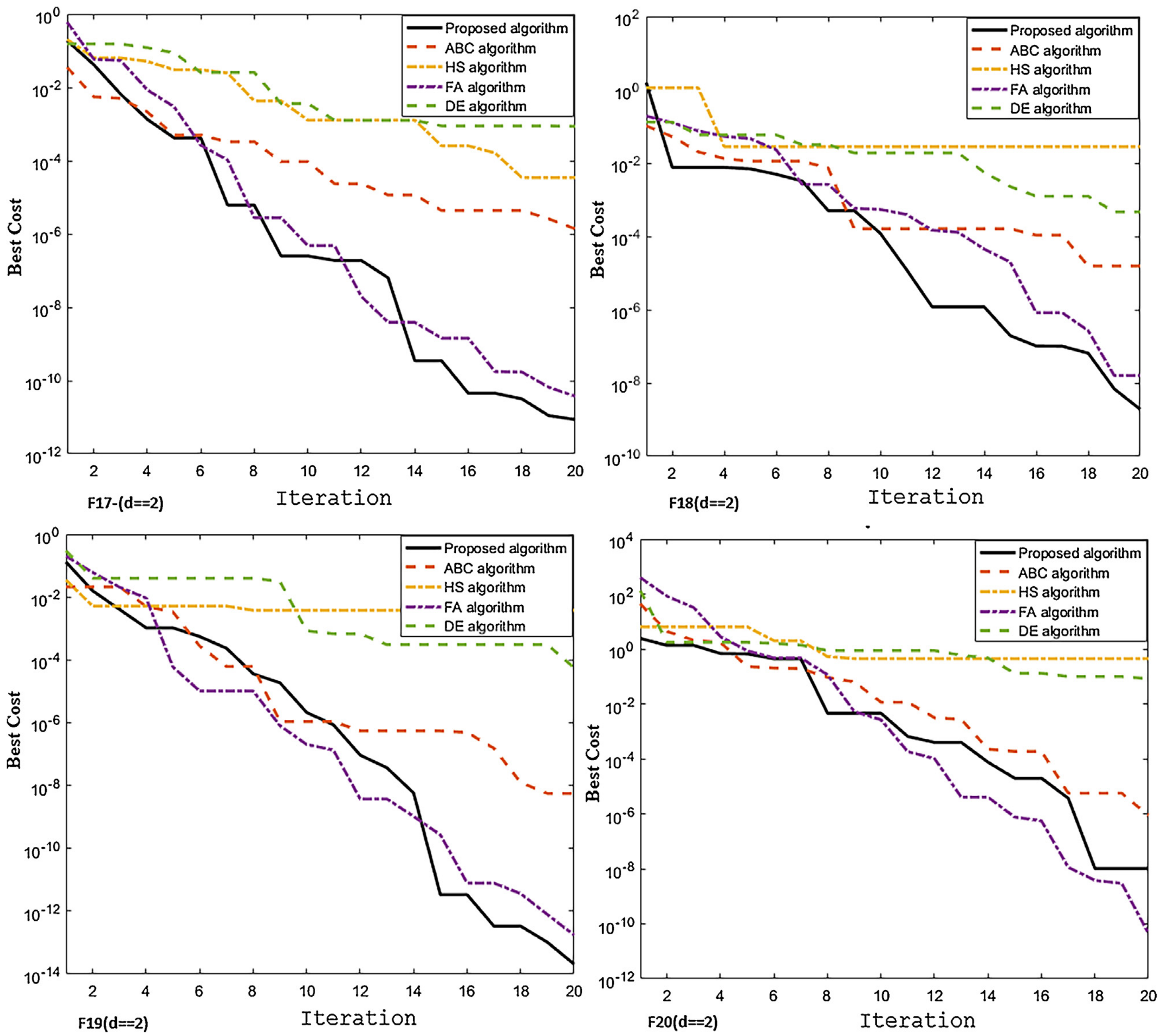

Fig. 4. The Amount of Convergence of the Farmland Fertility on the First F17-F20 with 2 Dimensions.

Table 6
Evaluation of Farmland Fertility and its Comparison with other Algorithms.

Function	Features	PSO [4]	MPSO [4]	BA [4]	Farmland Fertility
F01	4d-best	-	-	-	8.9013e-15
	10d-best	0.0132862	5.1833637e-12	0.0503454	4.8374e-12
	12-best	-	-	-	6.9938e-06
F04	20d-Best	-	-	-	0.9102587
	30d-Best	0.9381539	0.9946528	1.1610885	1.0588471
	40d-Best	-	-	-	2.5675001
F05	2d-Best	−1.9999994	−2	−1.9999692	−2
	5d-Best	-	-	-	0.99496
	10d-Best	-	-	-	3.2795
F07	2d-Best	-	-	-	8.8818e-16
	5d-Best	0.1040593	5.0789674e-9	5.3343711	4.4409e-15
	10d-Best	-	-	-	8.0033e-11
F09	2d-Best	-	-	-	1.2047e-07
	5d-Best	0.6330208	0.0031365	4.8972034	0.073926
	10d-Best	-	-	-	4.263300
F17	2d-Best	6.2606853e-9	3.0799861e-15	6.2922518e-6	8.254e-23
F18	2d-Best	2.2825886e-7	1.8163544e-13	1.0715264e-5	3.9904e-18
F19	2d-Best	7.7831913e-8	1.5198990e-15	1.8027111e-5	1.7817e-30
F20	2d-Best	1.1801626e-4	2.5424107e-14	0.1359886	2.2204e-16

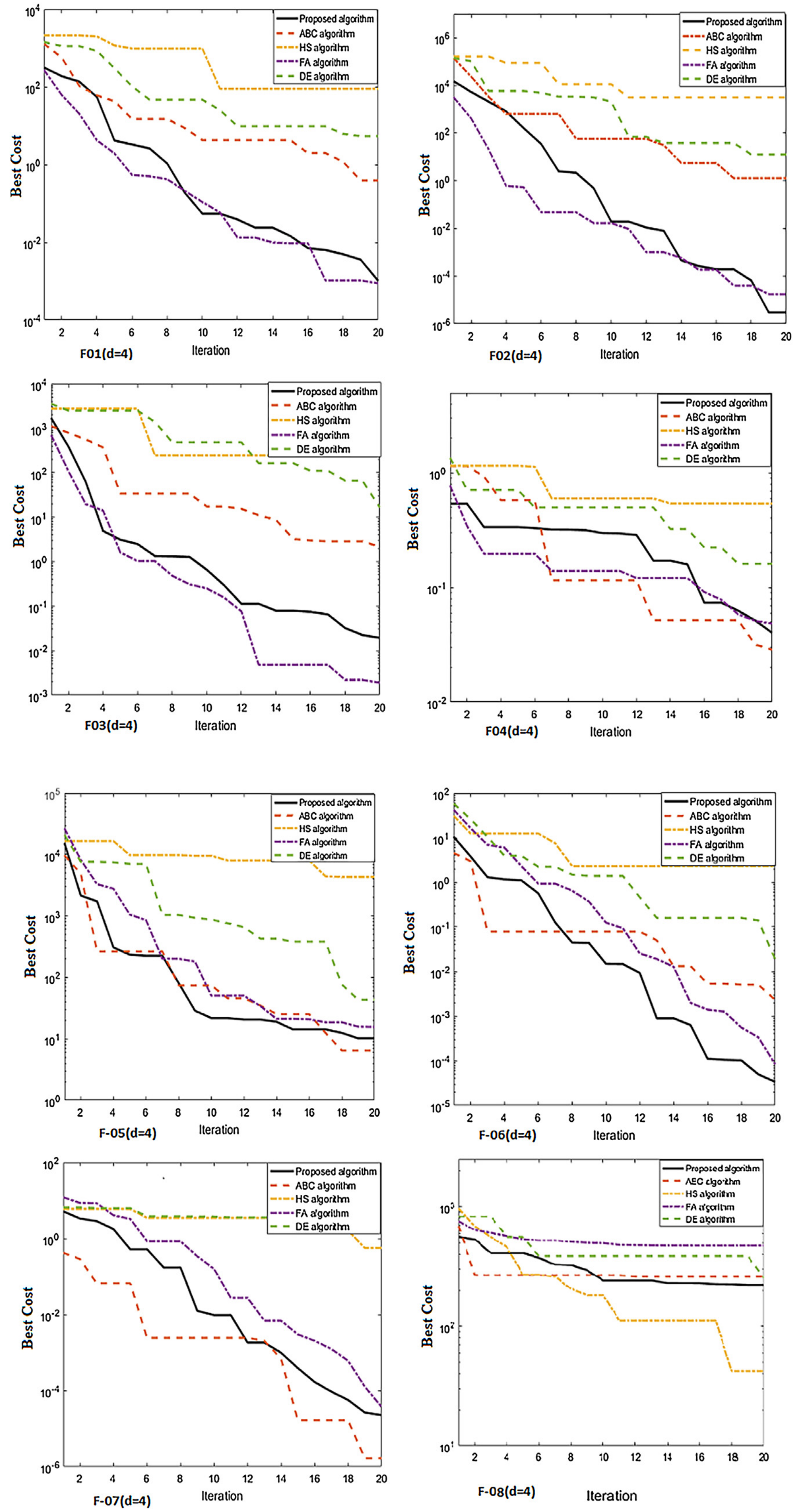

Fig. 5. The Amount of Convergence of the Farmland Fertility on the First F01-F08 with 4 Dimensions.

tility and other algorithms. In fewer dimensions, the algorithm has been able to show its superiority than other algorithms in more places. When the number of dimensions of the problem increases, the performance of other algorithms significantly decrease and the farmland fertility obtains better results than other algorithms. In order to do further investigation on the optimality of the farm-

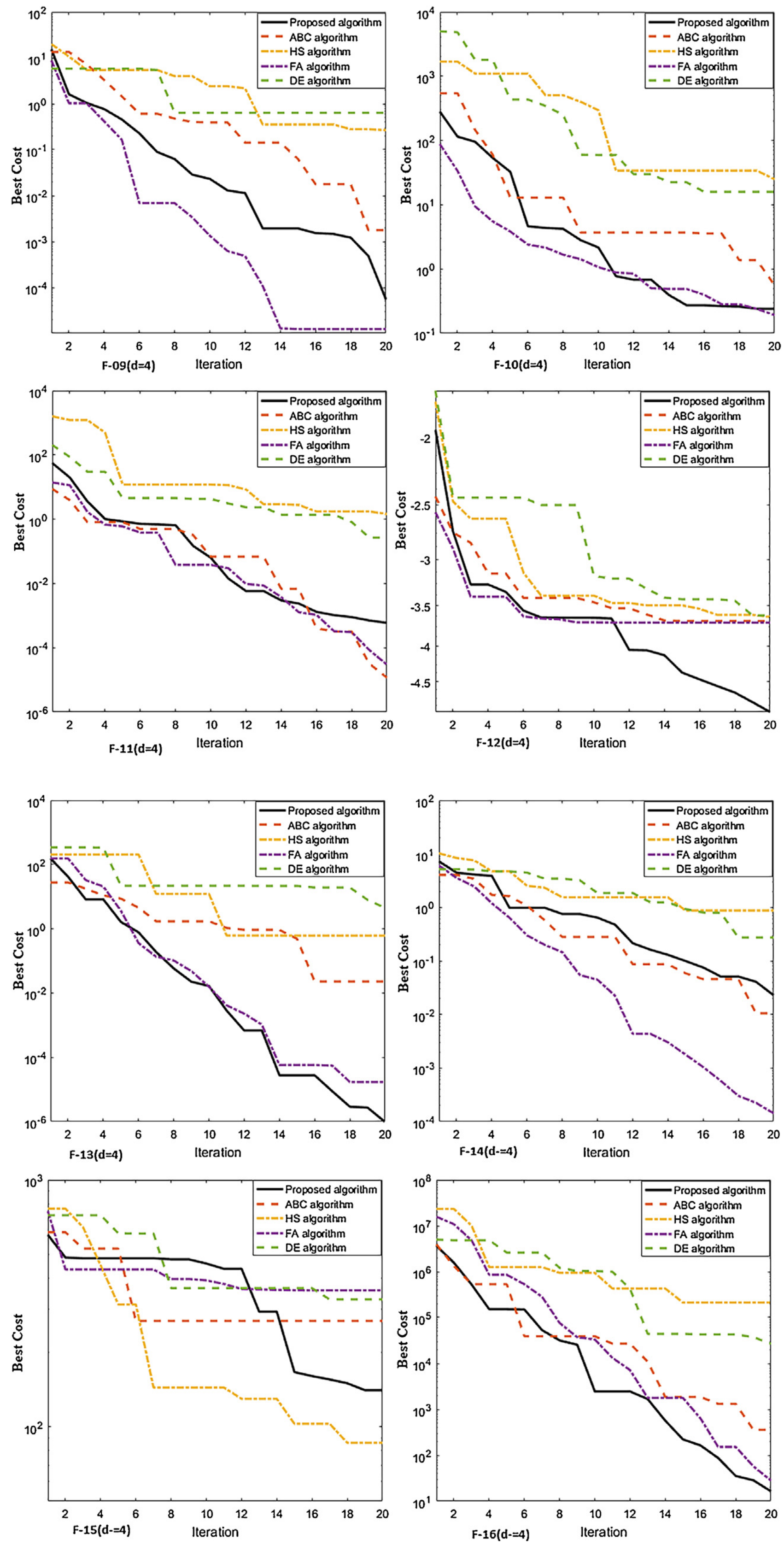

Fig. 6. The Amount of Convergence of the Farmland Fertility on the First F09-F16 with 4 Dimensions.

land fertility, we compared it with various benchmark functions used in public optimization problems that in the new paper in the field of metaheuristic algorithms is introduced [72]. In this paper, the results of the metaheuristic algorithms including PSO and BAT were implemented on 9 functions of optimization and the results of this paper are presented in Table 6. The benchmarks include

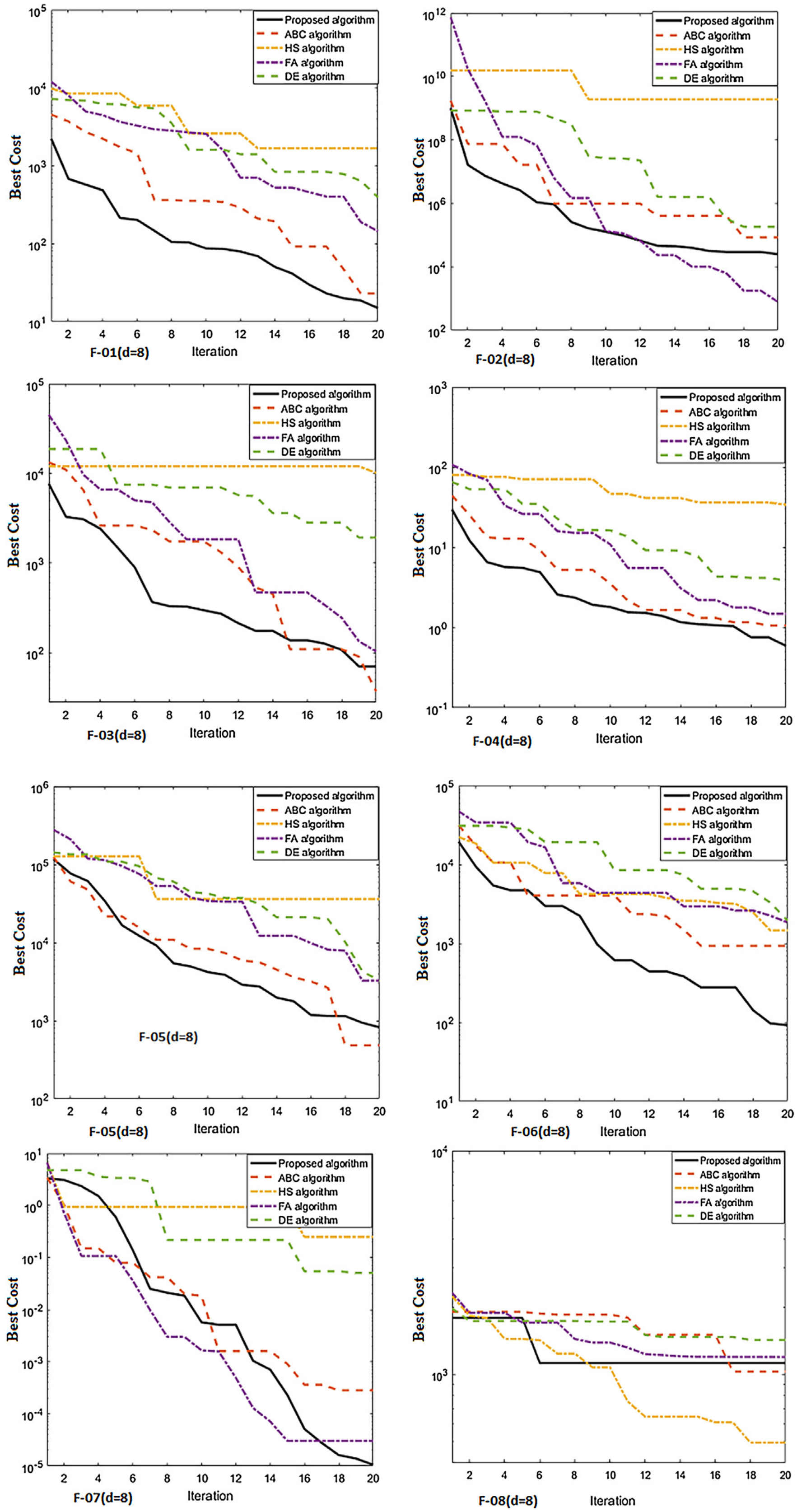

Fig. 7. The Amount of Convergence of the Farmland Fertility on the First F01-F08 with 8 Dimensions.

single-modal and multi-modal functions (16). In the [72] for the two-dimensional problems, they considered 2000 evaluations for the functions with the size of the population equal to 20. Furthermore, they have used 10,000 evaluations of the fixed functions for multidimensional problems, with the population size that was equal to 50 and used parameters of standard particle optimization

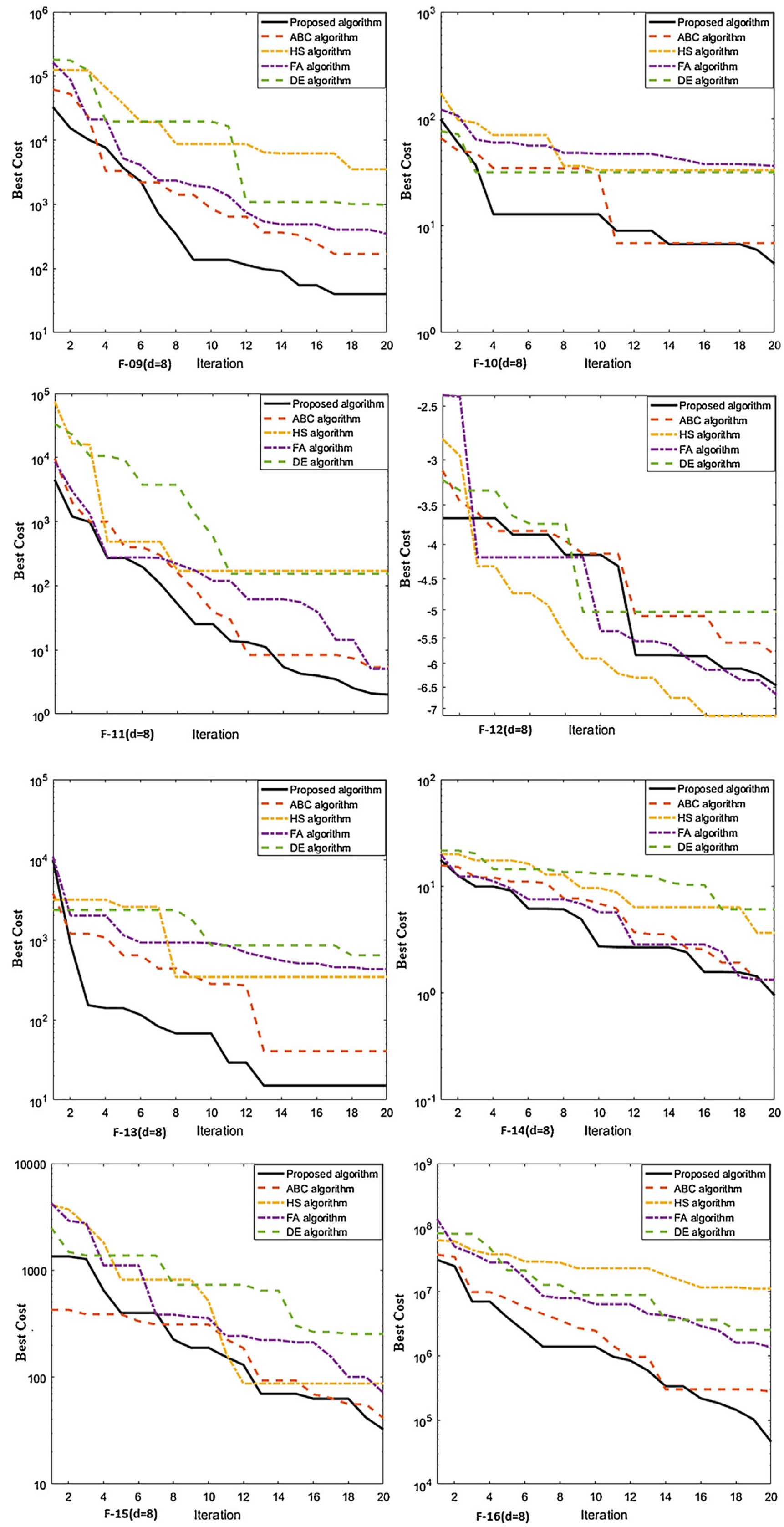

Fig. 8. The Amount of Convergence of the Farmland Fertility on the First F09-F16 with 8 Dimensions.

with acceleration coefficient equal to $\phi_1 = \phi_2 = 2.0$. However, to optimize the modified particles, the acceleration coefficient equal to $\phi = \phi_2 = 1.5$ was determined. Inertia weight equal to $\omega = 0.7$ was determined. Furthermore, the standard version of the BA was used with a limitation of loudness reduction $\alpha_b = 0.9$ constant expansion of rate plus $\gamma_b - 0.9$ and frequency was drawn uniformly

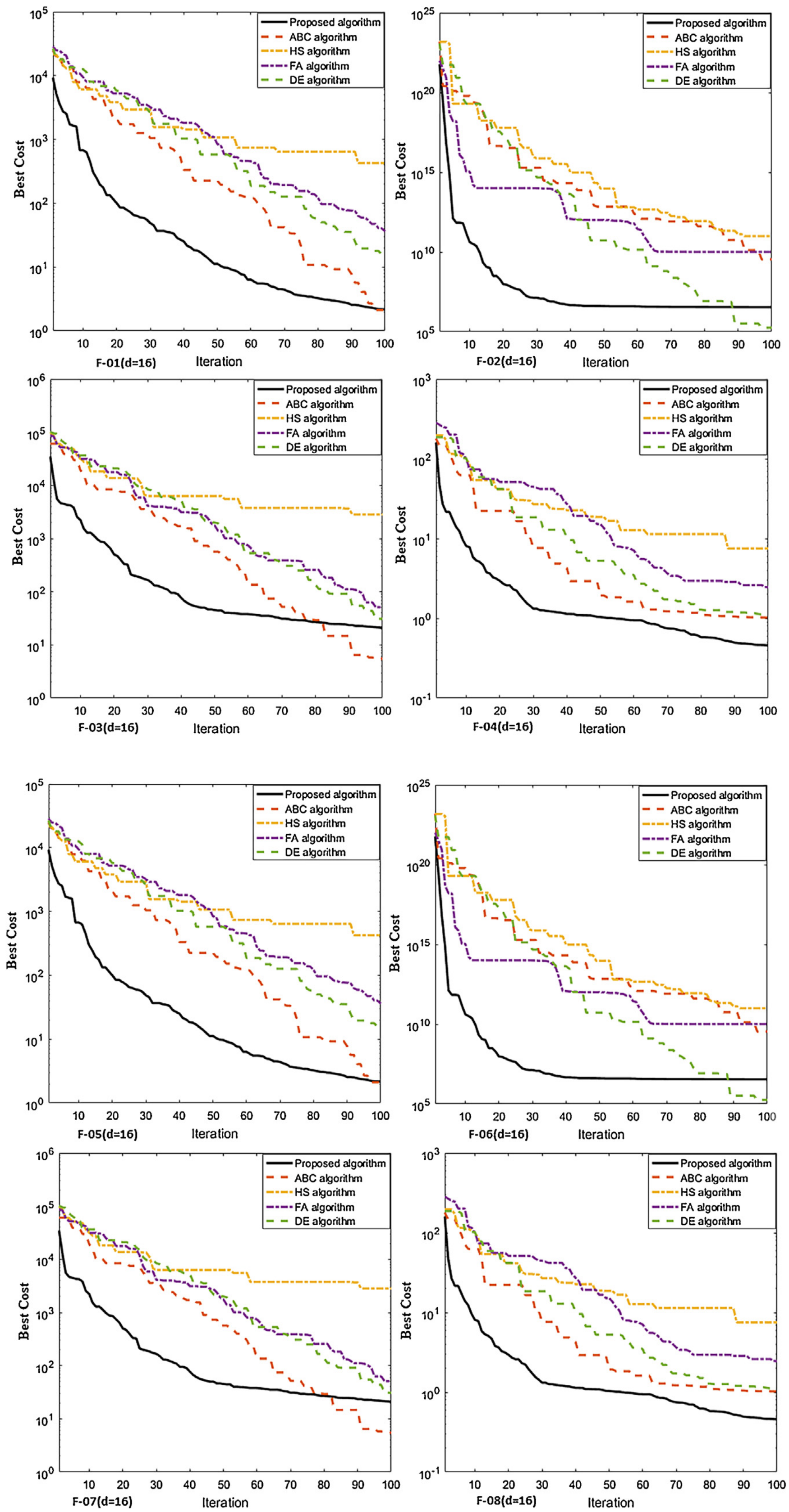

Fig. 9. The Amount of Convergence of the Farmland Fertility on the First F01-F08 with 16 Dimensions.

from 0 to 2 [0,2]. According to [72], we considered farmland fertility for two-dimensional problems with 2000 evaluations of functions and population size of 20 and considered 10,000 evaluations of the fixed functions with population size of 50 for multidimensional problems. Then, we determined parameters of the farmland fertility equal to $\alpha = 0.9$, $\beta = 0.8$, $W = 1$ and $Q = 0.6$. Finally, we performed

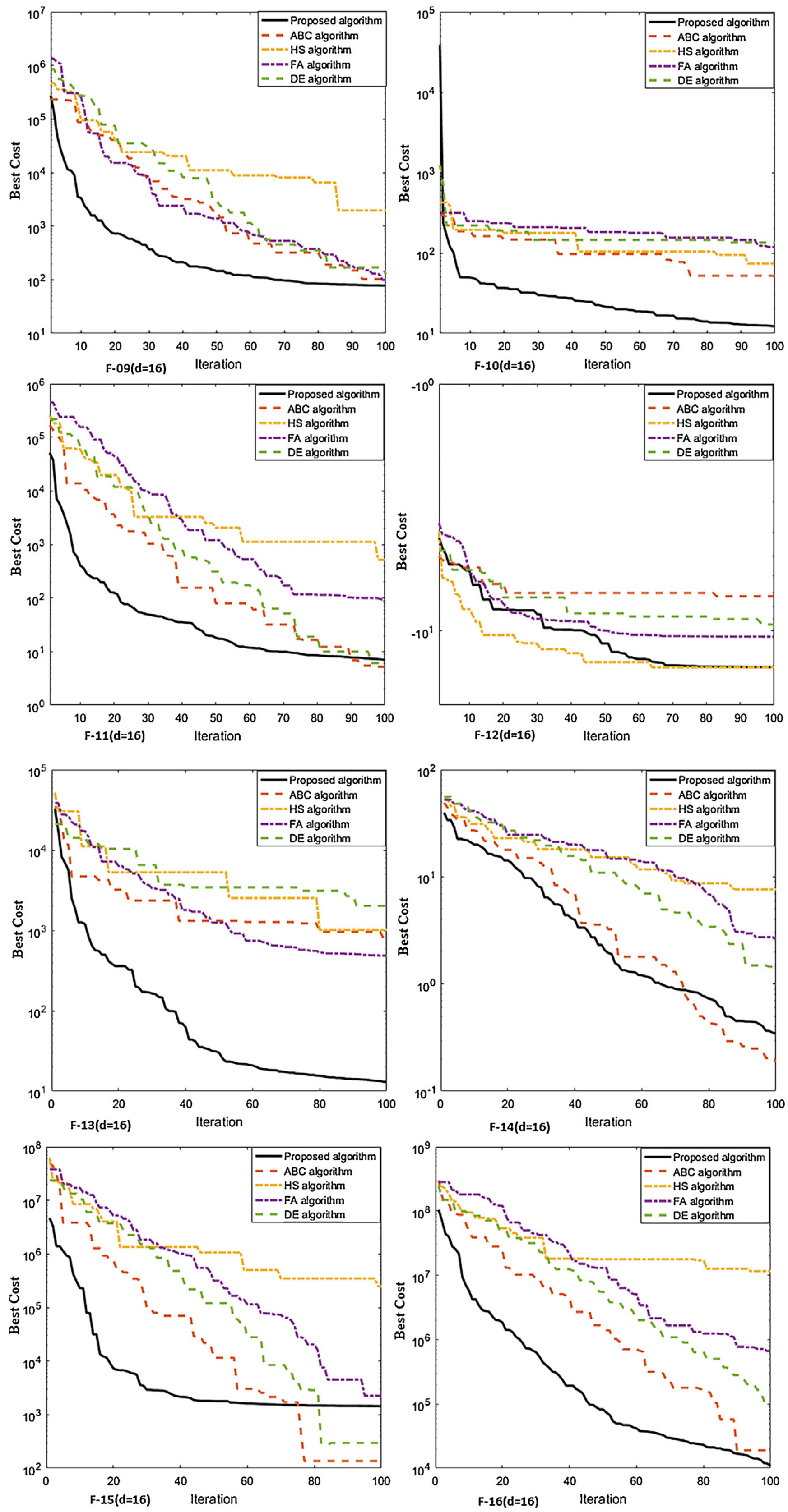

Fig. 10. The Amount of Convergence of the Farmland Fertility on the First F09-F16 with 16 Dimensions.

the farmland fertility on the functions given in Table 6 according to the two-dimensional and multi-dimensional problems and have added its results in the last column of Table 6.

We compared the farmland fertility with the various functions used in general optimization problems that in [59] have been introduced. In this paper, we implemented the results of metaheuristic

Table 7
Parameters of each of the comparative algorithms according to [59].

HS	The HS is a standard algorithm [10] which is described with these settings: $bw = 0.2$, $HMCR = 0.95$, $PAR = 0.3$
GA	The standard GA [73] with the probability of intersection of 0.95 and the probability of mutation of 0.05.
DE	Classical DE are described in [20] with the strategy of Ďe / Rand / Bin. The parameter settings are as follows: CR = rand [0.2.0.9], F = rand [0.4.1].
Farmland Fertility	The parameters of the farmland fertility are equal to w = 1, Q = 0.6 and β = 0.8, α = 0.9 and N = 30 (k = 2, n = 15).

algorithms such as; HS, GA, and DE on 16 functions of optimization and presented the results of this paper in Table 8. Parameters of each of the comparative algorithms according to [59] are available in Tables 7 and 8. Furthermore, because the number of functions and the number of evaluations of the initial functions and parameters were not equal in [72] and [59], we showed each one in separate tables:

In [59], for a fair comparison, common parameters were considered equally. The size of the population was determined equal to 30, the number of evaluations of the function was equal to 1500, and initial evaluations were not calculated. Although, all algorithms are randomly initialized with a similar method. Therefore, we determined tmax equal to 500. Based on this paper, we implemented farmland fertility on the functions given in Table 8 and with respect to two-dimensional and multidimensional problems and added its result in the last column of Table 8. Furthermore, the number of evaluations of function for the farmland fertility is considered to be = 1500.

The results of Tables 6 and 8 display the farmland fertility that is implemented on the 20 standard functions in Table 2. We compared farmland fertility with powerful algorithms such as; PSO, improved PSO, BA, GA, HS, and DE in large and small dimensions and on the standard function of optimization. The farmland fertility has succeeded in solving problems with smaller dimensions, like a strong metaheuristic algorithm such as: GA, improved PSO and sometimes, it even works much better than these algorithms, and optimizes problems nicely. Furthermore, the farmland fertility has been able to perform better than other algorithms in larger dimen-

Table 8
Evaluation of Farmland Fertility and Its Comparison with other Algorithms.

Function	Features	HS [5]	GA [5]	DE [5]	Farmland Fertility
F01	10d-best	-	-	-	6.3576e-013
	20d-best	-	-	-	0.1798E-01
	30d-best	5.919E+03	5.517E+00	2.481E+01	2.6571E+00
F02	10d-best	-	-	-	0.6497E+00
	20d-best	-	-	-	214036E+00
	30d-best	2.573E+33	7.488E+04	9.080E+08	2.3221E+06
F03	10d-best	-	-	-	1.0496e-07
	20d-best	-	-	-	9.4071E-01
	30d-best	4.124E+04	8.280E+01	9.877E+01	1.06824E+01
F04	10d-best	-	-	-	4.2780E-3
	20d-best	-	-	-	2.5874E-2
	30d-best	4.375E+01	1.080E-01	9.989E-03	1.03149E-01
F05	10d-best	-	-	-	1.6394 E+00
	20d-best	-	-	-	7.4641E+00
	30d-best	1.330E+02	2.994E+01	2.998E+01	3.1277E+01
F06	10d-best				8.7355e-07
	20d-best				1.2745e-3
	30d-best	1.366E+01	1.093E+00	1.053E+00	6.7768E-2
F07	10d-best	-	-	-	7.9936e-15
	20d-best	-	-	-	1.5377e-09
	30d-best	1.338E+01	2.595E+00	2.302E+00	9.582e-05
F08	10d-best	-	-	-	6.38E+01
	20d-best	-	-	-	1.636E+03
	30d-best	2.281E+03	2.736E+03	4.745E+03	3.957E+03
F09	10d-best	-	-	-	2.241E+00
	20d-best	-	-	-	4.899E+01
	30d-best	8.437E+04	1.048E+02	4.637E+02	2.371E+02
F10	10d-best	-	-	-	0.4757E+00
	20d-best	-	-	-	1.2038E+01
	30d-best	2.960E+02	1.122E+01	1.414E+02	3.60277E+01
F11	10d-best	-	-	-	0.49062E+00
	20d-best	-	-	-	9.2627E+00
	30d-best	4.057E+04	1.207E+01	2.650E+01	4.5644E+01
F12	10d-best	-	-	-	−8.9921E+00
	20d-best	-	-	-	−1.11411E+01
	30d-best	−1.477E+01	−2.473E+01	−1.259E+01	−2.79383E+01
F13	10d-best	-	-	-	0.6886E+00
	20d-best	-	-	-	9.8634E+00
	30d-best	1.269E+04	7.206E+01	2.073E+03	7.2449E+01
F14	10d-best	-	-	-	6.7865E-08
	20d-best	-	-	-	4.5684E-03
	30d-best	9.950E+00	1.029E-01	1.271E+01	8.3781E-02
F15	10d-best	-	-	-	0.6886E+00
	20d-best	-	-	-	9.8634E+00
	30d-best	3.915E+02	2.611E+02	2.948E+02	7.2449E+01
F16	10d-best	-	-	-	0.77976E+00
	20d-best	-	-	-	8.66099E+02
	30d-best	6.110E+07	1.474E+06	1.283E+05	2.3128E+04

sions. The efficiency of other algorithms is significantly reduced by increasing the number of dimensions of the problem. However, the farmland fertility obtains better results than other algorithms.

6. Conclusion

In this paper, we presented a new metaheuristic algorithm that is named the farmland fertility, which is a population-based nature-inspired algorithm. It is classified in the category of memory usage algorithms due to the optimal use of both types of internal and external memory. The farmland fertility was divided into six distinct stages, each of the stages was presented theoretically to solve continuous optimization problems, and finally, they were formulated and described. The proposed metaheuristic algorithm divided the search space into several sections and based on information it gains the available solutions in the section. The considered changes according to the stages of the farmland fertility are applied individually on the solutions of each section. The proposed metaheuristic algorithm is very simple and very flexible than other available metaheuristic algorithms. Furthermore, the point of differentiation and the power of the farmland fertility to other algorithms is partition of the search space and using two types of internal and external memory along with each section that how to use both of these memories in the farmland fertility has played a major role in optimizing problems. On the other hand; how to change on each section and the part that has already had the worst possible result, are specific features of the farmland fertility which cause this algorithm completely differs from other metaheuristic algorithms. This feature causes in the sections and because of it we have achieved the better result; is decreased the step size for a random walk and it happens around the best position that is determined by the external memory, and in the sections that we have achieved the worst result; we can easily do in the entire search space randomly. The proposed metaheuristic algorithm is evaluated by using large number of mathematical problem of standard benchmark and we compared it with other powerful metaheuristic algorithms such as: ABC, FA, HS, PSO, DA, BA and improved PSO. In this comparison, we observed that proposed metaheuristic algorithm is very promising and more powerful than existing algorithms. Furthermore, the complexity of this algorithm is less than PSO and BA.

Significant results of the farmland fertility caused us to consider the details of the farmland fertility in addition, its implementation on other functions as an appropriate topic for future researches. Further researches are required to do more evaluation studies in solving optimization problems, to discover the ability of the algorithm. Comparative studies with other metaheuristic algorithms, the difficult test functions, and real-world problems with complex limitations will show the strength and weakness of the algorithm. Furthermore, we can consider other research topics such as; the study of the sensitivity of parameters, how to use the internal and external memory of the farmland fertility, their effect on maintaining an optimal balance between heuristic phases and efficiency algorithm for optimization process. Furthermore, we can consider expansion of the improved version of the farmland fertility and other versions of the farmland fertility for multi-objective or discrete optimization problems and types of difficult problems as topics for future researches.

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