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A Novel Version of GSA and its Application in the K-of-N Lifetime Problem in Two-Tiered WSNs

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ABSTRACT: For the past decades, we have witnessed an extraordinary advancement in the field of Wireless Sensor Networks (WSNs) in both academic and industrial settings. Moreover, the network lifetime is regarded as one of the most critical issues in this field, and quite a large number of researchers are increasingly exploring this topic of interest. In this study, the linear-scaling method is initially implemented onto the Gravitational Search Algorithm (GSA) for the mass calculation. This is due to the fact that the exploitation and exploration abilities of the algorithm can be fully controlled using this approach. The results obtained from the simulation revealed that this novel GSA achieves the same level of performance as that of conventional GSA and significantly outperforms the state-of-the-art meta-heuristic search algorithms. Additionally, this improved GSA can be readily utilized to solve the K-of-N lifetime problem in two-tiered WSN architecture. In our proposed method, the novel GSA was employed in order to find the optimum location of the base station to enhance network lifetime. Furthermore, the simulation results indicated that despite the simplicity in implementation, our proposed method has a higher level of performance compared to other approaches used to address K-of-N lifetime problem in two-tiered WSN architecture.

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1. Introduction

Over the past few decades, we have witnessed a significant advancement in the field of Wireless Sensor Networks (WSNs) in both academic and industrial settings. Moreover, a large number of sensor nodes are deployed and networked in order to monitor and screen the target area. This is performed in a manner that the data of interest can be sensed, processed, stored, and finally collected. Furthermore, numerous potential applications of WSNs have been explored in the fields of environmental engineering [1], healthcare [2, 3], industry [4], military [5], object detection and tracking [6], leak detection in pipelines [7], smart housing [8], and green or sustainable buildings [9].

WSNs essentially consist of hundreds or thousands of inexpensive sensors. These sensor nodes can be deployed manually or randomly in the target area. Moreover, they are all equipped with sensing, communicating, processing, and power unit components. They basically sense the data distributed in the target area, then process the raw data and finally transport them to a designated node, also known as the Base Station (BS). These sensors have rather limited energy resources, and battery replacement is impossible in the areas in which they are being utilized. Thus, energy consumption optimization of the WSN protocols and network lifetime improvement are two of the most critical issues in this field of research. Additionally, clustering is one of the most popular approaches to enhance energy efficient protocols of WSNs.

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In this approach, sensors are grouped into several clusters; each cluster has a unique sensor node, considered as its cluster head, where the sensors in each of the clusters transport their sensed data to this sensor node. Furthermore, the cluster head receives all of the raw data originated from the cluster nodes, compresses the data and finally transports them to the base station. It should be noted that clustering protocols improve the network lifetime by minimizing the number of nodes which take part in long-distance communications. Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol is one of the most popular methods used in the clustering protocols of WSNs [10].

However, the optimal number of cluster heads cannot be determined using the LEACH protocol. LEACH-C protocol can improve the performance of LEACH by specifying the cluster heads in each round of the base station using a centralized algorithm [11]. Moreover, two-tiered architecture can be used in energy-efficient clustering protocols of WSNs. On the other hand, a two-tiered wireless sensor network contains a large number of sensor nodes which sense the data from the target area and grouped them in different clusters. Each cluster in the two-tiered architecture possesses at least one Application Node (AN) that its primary purpose is to process long-distance data transitions. Furthermore, these nodes have more energy compared to sensor nodes and each network contains a base station which collects the data from every application node. There are several key assumptions when dealing with this type of WSN architecture. For instance, application nodes might be aware of the location and remaining energy level of this architecture, moreover, the base station has unlimited energy resources [12].

There are numerous approaches for minimizing the energy consumption of WSNs [13]. In a conducted study [14], an efficient approach for clustering and distributing multi-hop routing protocol was investigated. This protocol consists of the cluster head selection algorithm, a cluster formation scheme, and a routing algorithm for the data transmission between the cluster heads and the base station. Moreover, in another carried out study [15], an approach was proposed which provides an optimum distribution of the cluster head among the sensor nodes and avoids repeated selection of cluster heads. This was based on the Received Signal Strength Indication (RSSI) and the residual energy level of the sensor nodes. In addition, in a performed research by Pan et al. [16], the topological network lifetime of WSNs was deterministically maximized. This was performed by proposing algorithmic approaches to optimally locate base stations even when the initial energy provisioning of the application nodes was no longer proportional to their mean bit-stream rate.

Recently, meta-heuristic search algorithm has been widely implemented in WSNs protocols in order to optimize the energy consumption of the nodes. For example, Hybrid Harmony Search Algorithm (HHSA) and Particle Swarm Optimization (PSO) were utilized in a study [17] to improve the performance of the LEACH algorithm in an energy-efficient clustering protocol. In this research, the high performance of HHSA search efficiently and the dynamic capability of PSO were integrated to enhance the whole network protocol performance. In a conducted study [18], a new method was introduced for the routing problem which essentially is an NP-hard problem based on variable dimension particle swarm optimization. In [18], the genetic algorithm was utilized to provide a proper balancing between several properties of the networks such as the remaining energy, distance to the base station, the number of nodes in the vicinity, and the expected energy expenditure. Thus, this protocol is able to significantly improve the network lifetime. Moreover, the PSO algorithm was employed in another study [19] to solve the K-of-N lifetime problem. In another research [20], the genetic algorithm was implemented to find the optimum application node in each cluster of the two-tiered WSNs and also to discover the optimum routing path in order to minimize the energy consumption of the network.

The gravitational search algorithm is, in fact, a novel heuristic algorithm which is basically inspired by Newton's law of gravity. This algorithm was proposed by Rashedi et al. [21, 22], and is being applied to a large number of real-world applications such as neural network [23], robotics [24], and WSNs [25, 26]. In this research, we first utilize the linear scaling function to improve the GSA performance. It should be noted that linear scaling is essentially used to balance the exploration and exploitation abilities of the GSA. Then, the proposed algorithm is employed to provide a solution for the K-of-N network lifetime problem.

The remaining sections of this paper are organized as follows. A number of preliminary definitions and basic concepts are briefly introduced in sections 2. In section 3, the improved GSA is fully presented. K-of-N network lifetime problem is then solved using this very improved GSA in Section 4. Finally, the obtained results are reviewed and discussed in section 5, and section 6 presents the drawn conclusion.

2.Basic Concepts

This section contains a range of crucial information introducing the two-tiered wireless sensor networks and the associated energy model which is mainly used in this type of network, the gravitational search algorithm, and the linear scaling approach.

2.1 Two-tiered Wireless Sensor Network

A two-tiered wireless sensor network is essentially an architecture for WSN clustering protocols, as shown in Figure 1. In this architecture, the network consists of several clusters, which in turn, possess a number of sensor nodes and at least one application node. Moreover, sensor nodes can be regarded as small and rather cheap nodes which their main purpose is to sense the target area. In addition, these simple nodes directly transmit the raw data to the application node; that is to say, sensor nodes lack any type of communication with the other sensor nodes or the base station.

In each cluster, the application node collects the raw data which are originated from the sensor nodes of the same cluster. Then, the raw data are compressed and compacted by the application node, and the irrelevant data are simply deleted. At the next step, each application node transmits the compressed information of its associated cluster to the base station. Additionally, application nodes are able to maintain and control the status of sensor nodes (sleep, idle, or active) in each cluster.

A two-tiered architecture is depicted in Figure 1.b. One can readily observe the concept that the raw data are acquired and compressed in the lower tier whereas the data are transmitted from the clusters to the base station in the upper tier. Both the sensor and application nodes are limited in energy resources while the cluster nodes can do their designated tasks until the application node is active and able to send the data to the base station. Although application nodes have a higher level of energy with respect to the sensor nodes, they tend to have more responsibilities. Consequently, consuming this limited energy in an efficient manner is one of the most critical issues of the energy-efficient clustering protocols of WSNs. For example, one of the commonly-occurred problems is the K-of-N lifetime problem (defined in two-tiered WSNs), where N application nodes are present and each of them has its own properties. Moreover, the network lifetime is meticulously determined when at least K application nodes are still active. In other words, the network fails when N-K+1 application nodes are inactive.

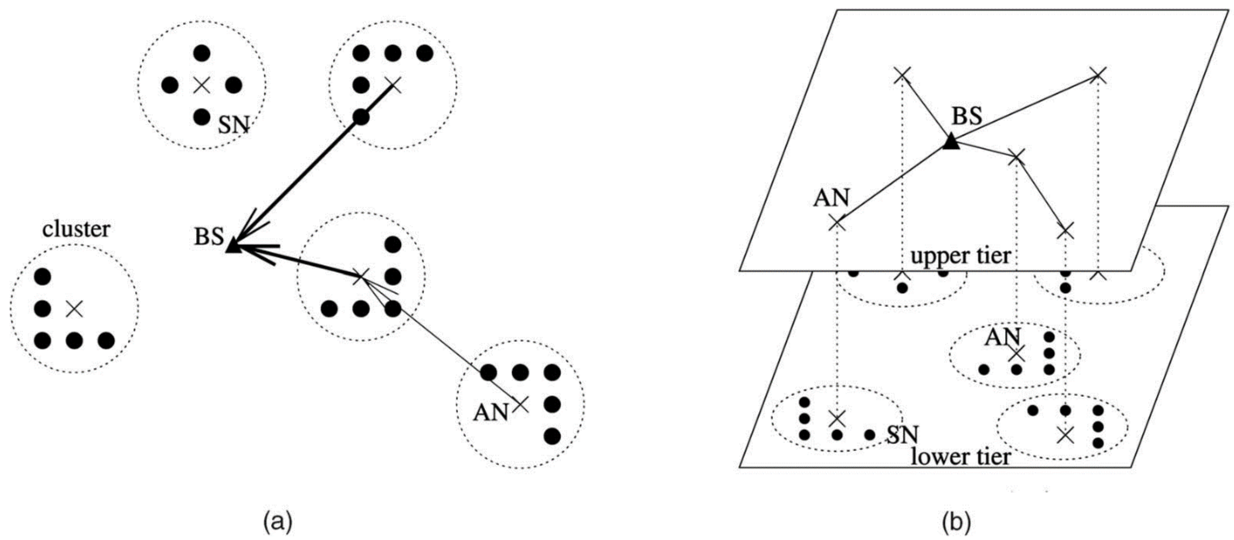


Fig. 1. The architecture of two-tiered wireless sensor networks [16].

The position and location of the application nodes can be fully obtained using GPS (global positioning system) receivers. Once this information is acquired, the primary concern is to find the optimum location of a base station in order to optimize the network energy consumption. In this study, we used an improved version of GSA to determine, firstly, the optimum location of a base station in a two-tiered WSNs architecture and secondly, the optimum solution to the K-of-N lifetime problem.

2.2 The Energy Model

In this research, we used the energy model as defined and employed in previously conducted studies [16]. In two-tiered networks, communication is considered one of the most vital sources of energy consumption. Additionally, base station nodes are not nearly energy constrained. Therefore, we primarily focused on the energy consumption of the application nodes in the two-tiered wireless sensor networks. The energy consumption in each time unit can be calculated using Equation 1.

$$p(r,d) = r(\alpha_1 + \alpha_2 d^n) \qquad (1)$$

where r is the information transmission rate, α_1 and α_2 are the distance-independent and distance-dependent parameters, respectively. Finally, d is the Euclidian distance between AN and BS. The distance-independent part of this formula is irrelevant to the BS position. Therefore, efforts were made in this paper to find the optimum location of BS. The distance-dependent parameter and its term were the primary area of focus.

Moreover, the network lifetime of each AN can be formulated as follows:

$$\int_{t=t_0}^{t_0+l} p(t)d(t) = e(0) \qquad (2)$$

where t_0 is the initial time associated with AN, l is the AN lifetime, p(t) is the energy consumption of this particular AN at time t, and e(0) is the initial energy and battery level of this specific application node. According to this equation, we can determine the lifetime of each application node using its initial energy and its rate of energy consumption.

2.3 Gravitational Search Algorithm

The gravitational search algorithm is one of the most recent meta-heuristic search algorithms proposed by Rashedi et al. in their carried out studies [21, 22]. This algorithm, which is mainly inspired the Newton's law of gravity, is being used in numerous applications and real-world optimization problems for which the classical methods are rendered useless, such as robotics [24], image processing [27], pattern recognition [28], and economics [29].

In this algorithm, the position of each agent represents a possible solution in the search area of the problem and the acquired mass value of each agent indicates the quality of that solution. The agents possessing heavier masses represent better solutions with respect to the lighter ones, therefore, they should attract other masses due to gravity. Moreover, the position of the i^{th} agent in n-dimensional search space is represented by $X_i=(x_i^1,x_i^2,\ldots,x_i^n)$. The value of the i^{th} mass in the iteration t is determined using Equation 3.

$$M_i(t) = \frac{fit_i(t) - worst(t)}{\sum_{j=1}^{n}(fit_j(t) - worst(t))} \qquad (3)$$

where $fit_i(t)$ is the fitness function value of the i^{th} agent, and worst(t) is the worst mass value in the iteration t. Based on the law of gravity, the total gravity force exerted on the i^{th} agent in the d^{th} dimension at time t is computed using Equation 4.

$$F_i^d(t) = \sum_{j\in Kbest, j\neq i} G(t)\frac{M_i(t).M_j(t)}{R_{ij}(t)+\varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \qquad (4)$$

where K best is the set of K best solutions including the heavier value of masses while its value is a function of time (t). Moreover, ε is a small constant preventing a zero denominator and R_{ij} (t) is the Euclidian distance between the agents i and j in the d^{th} dimension. It should be noted that the acceleration, velocity, and the position equations of the agents in the d^{th} dimension at iteration t+1 can be obtained based on the law of motion (Equation 5-7) [21].

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \ , \tag{۵}$$

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{۶}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \ . \tag{۷}$$

The general principles of GSA are demonstrated in detail in Figure 2.

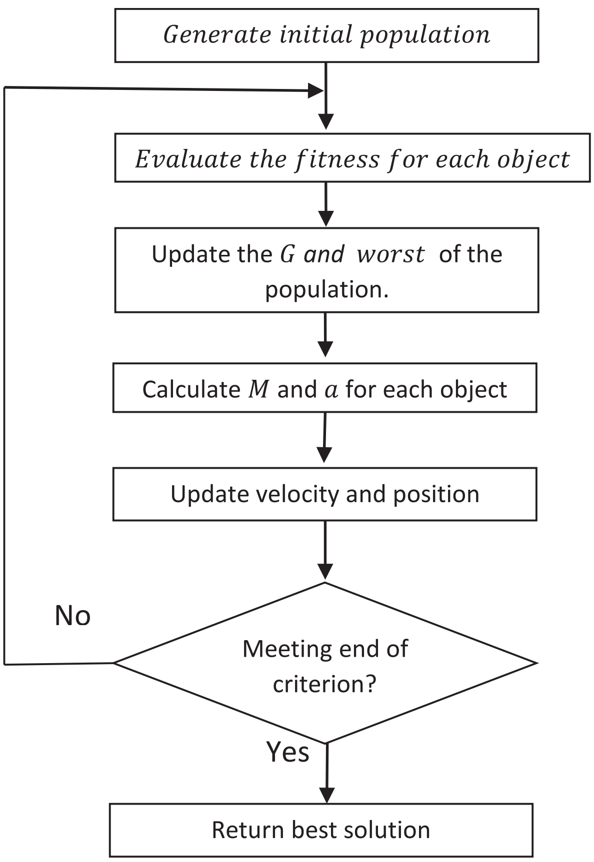


Fig. 2. General principles of GSA [21].

2.4 Linear Scaling

Linear scaling is one of the most useful and efficient scaling methods despite its simplicity in implementation. Furthermore, scaling methods are used in a large number of applications and problems in which the range of fitness values for the agents are either too large or too small. If the range of fitness value for the agents is rather large, the selection pressure is then high. Thus, the optimization algorithm may face a premature convergence and becomes trapped in a local optimum. Moreover, provided that the fitness function range is too small for the optimization algorithm agents, the selection pressure is then low which causes a low rate of convergence in the algorithm. In these problems, the fitness value of each agent is scaled, and then the algorithm is performed for each iteration. Consequently, the exploration and exploitation abilities of the algorithm can be fully controlled by a scaling method.

In the linear scaling method, the selection expectation rate of the optimum agent in the population is controlled with respect to the specific agent possessing the mean fitness value in that iteration. Linear scaling of the fitness value for the i^{th} agent in the t^{th} iteration is determined using Equation 8.

$$fit_i^s(t) = a(t) \times fit_i(t) + b(t) \tag{۸}$$

where fit_i^s (t) is the scaled fitness of the agent and fit_i (t) is a fitness value of the agent prior to scaling, which is determined by the fitness function in the optimization algorithm. Moreover, a(t) and b(t) are functions computed as follows:

$$a(t) = \frac{(C_m - 1) fit^{ave}(t)}{fit^{max}(t) - fit^{ave}(t)} \ , \tag{۹}$$

$$b(t) = (1 - a(t)) \times fit^{ave}(t) \tag{۱۰}$$

where fit^{ave} (t) is the mean fitness values of the population agents in the t^{th} iteration, and fit^{max} (t) is the maximum fitness value of the agents in the t^th iteration. Furthermore, C_m is defined as the ratio of selection expectation of the optimum agent to that of the mean fitness value of the population, which is formulated in Equation 11.

$$fit^{s,max}(t) = C_m \times fit^{s,ave}(t) \tag{۱۱}$$

The C_m ratio is defined over the interval of [1, 2]. For instance, if C_m is equal to 2, the selection expectation of the optimum agent is twice as that of the agent possessing the mean fitness value.

In each iteration, the optimization algorithm determines the fitness value of each agent using the predefined fitness function. At the next step, the scaling method is implemented onto the fitness values of the agents. Finally, the algorithm is once again continued using the newly-obtained scaled fitness values. Hence, the exploration and exploitation abilities of the optimization algorithm can be controlled and screened using this method.

3- Modified GSA Using Linear Scaling

The value of masses has a vital role in the performance of GSA. The abilities of this algorithm, such as exploration and exploitation can be controlled using a proper definition of mass values. At the beginning of the algorithm, it is rather beneficial to have a high level of exploration ability to avoid any premature convergence. Thus, the variance of masses should be kept at a minimum value and the masses should have relatively close values. However, as the algorithm reaches toward its end, the exploitation power of the search algorithm should be increased in order for the algorithm to converge toward the optimum solution. Thus, the variance of masses should essentially be maximized. More dense masses can obviously attract other masses, and the algorithm converges to the optimum solution using the heaviest available mass.

In the standard GSA, the value of masses is equal to the value of the normalized fitness function of the agents, which is determined using Equation 3. In this study, we used a linear scaling scheme for the process of mass calculation in order to control the exploitation and exploration abilities of the algorithm and consequently improve the performance of the algorithm. Therefore, the value of the ith mass in the improved GSA and the proposed method is defined as the following equation:

$$M_i(t) = a(t) \times fit_i(t) + b(t) \tag{۱۲}$$

where fit_i (t) is the fitness function value for the i^th agent in the tth iteration. In addition, a(t) and b(t) are the two functions described in section 2.4.

In order to control the exploration and exploitation abilities of the algorithm, C_m should be a function of time and iteration of the algorithm. Moreover, C_m should be low at the beginning of the algorithm when the exploration ability is much more in demand. Thus, the selection pressure of the algorithm should be reduced so that the algorithm would be able to explore the feasible area in order to find the optimum solutions. On the other hand, as the algorithm reaches toward the end, it should converge toward the optimum solution and exploitation ability, therefore, it is advisable to have a relatively high value for the C_m ratio. Thus, the selection pressure is rather high and the algorithm converges toward the optimum solution. Consequently, the C_m ratio should be a function of the algorithm time and is defined using Equation 13.

$$C_m = \sqrt{\frac{t}{\max t}} + 1 \tag{۱۳}$$

where t is the number of iterations in the algorithm and maxt is the maximum number of iterations in the algorithm. Moreover, at the beginning of the algorithm, C_m is low in value (around 1), selection pressure is also low, and the exploration ability is quite high. Thus, the algorithm explores the entire feasible area. On the other hand, as the algorithm reaches toward the end, the C_m ratio increases and exerts a significant force on the algorithm to converge toward the optimum solution. Thus, it was shown that the linear scaling could improve the GSA performance by controlling the abilities of the algorithm.

4-Solving the K-of-N lifetime problem

In this section, the modified GSA and the proposed algorithm are employed to solve the K-of-N lifetime problem in the two-tiered wireless sensor networks. In the real-world applications and problems, application nodes have various properties, such as initial energy, transmission rate, and specified values of their parameter. In this type of settings, finding the optimal location of the base station is rather difficult. Therefore, we use a proposed search algorithm to locate the optimal position of the base station.

The lifetime of application node j, denoted by l_{ij} (t), with respect to the ith agent of the proposed search algorithm and in the tth iteration is determined using Equation 14.

$$l_{ij}(t) = \frac{e_j(0)}{r_j(a_{j1} + a_{j2} d_{ij}^n)} \tag{۱۴}$$

where e_j (t) is the remaining energy of the jth application node in time t and e_j (0) is the initial energy of this application node. Moreover, r_j is the data transmission of the application node j. In addition, a_j1 and a_j2 are the distance-independent and distance-dependent parameters of the jth application node, respectively. Finally, d_{ij}^n is the nth-order Euclidian distance from the j^th application node to the ith agent.

Given the K-of-N lifetime problem in a two-tiered WSNs architecture, N application nodes are considered while having their own specific properties. The entire network is active until at least K application nodes are still alive. On the other hand, the network ceases to operate when N-K+1 application nodes become inactive or run out of energy. Thus, the fitness function was used to evaluate the proposed algorithm agent and is defined by Equation 15.

$$fit(i) = \min_{j=1,\dots,N} {}_{N-K+1}\{l_{ij}\} \tag{۱۵}$$

In this study, the gravitational search algorithm alongside the linear scaling method for mass calculation was employed to maximize the fitness function and find the optimal location of the base station. Based on the K-of-N problem, the network fails when N-K+1 application nodes are rendered inactive. Thus, the primary purpose of this fitness function is to maximize the lifetime of the (N-K+1)th application node since the network lifetime is a direct function of this particular AN lifetime. Moreover, an agent possessing a higher value of this fitness function is considered a better solution to the problem due to a higher increase in the network lifetime. Therefore, according to this fitness function, the location of the optimum agent is, in fact, the optimum location of the base station in a two-tiered WSN architecture with a maximized lifetime.

First, all agents are randomly distributed over the feasible solution area, where each agent presents a possible location of the base station. Then, the fitness function is evaluated for each agent according to Equation 15. The value of masses is determined using sigma scaling based on Equation 12. Finally, the masses attract each other due to their gravity and move toward the feasible solution area. These procedures are repeated until the termination condition is reached. Figure 3 shows the flowchart of the proposed method which was performed to find the best location of the base station in the K-of-N lifetime problem in a two-tiered WSN architecture.

5- Results and Discussion

In this section, the performance of the proposed search algorithm, described in section 3, is initially evaluated and compared with a number of common and state-of-the-art

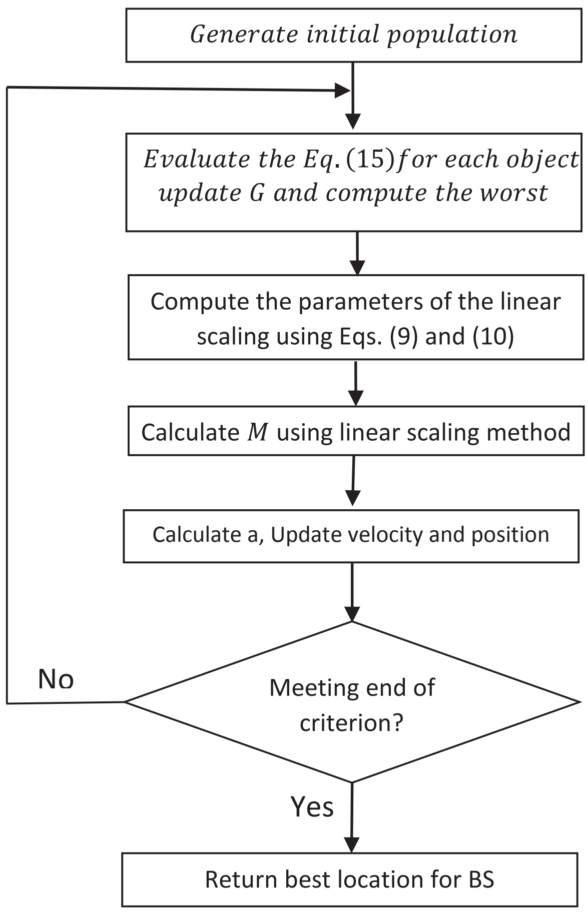


Fig. 3. Adaptive proposed algorithm for finding the optimum BS location.

meta-heuristic search algorithms. Subsequent to obtaining the simulation results, a statistical test is used to analyze them. Then, this algorithm is employed to solve the K-of-N lifetime problem in a two-tiered WSNs architecture demonstrated in section 4. Finally, the simulation results are compared with other standard methods.

5.1 The Modified Algorithm

In this subsection, the performance of the proposed method (LS-GSA) is investigated using standard benchmark functions (CEC) [30]. Moreover, this benchmark test function contains three classes of test functions, including unimodal test functions (F_1-F_5), basic multimodal test functions (F_6-F_{20}) and composition test functions (F_{21}-F_{28}). The properties of these test functions are described in more detail in a number of conducted study [30-32]. The obtained results are compared with several popular and state-of-the-art optimization algorithms, such as Joint Approximation Diagonalization of Eigen-matrices (JADE) [33], gradient-based PSO, which can be regarded as one of the new versions of PSO algorithm [34], GSA [21], Disruption-GSA [35], BlackHole-GSA [35], and clustered-GSA [36]. It should be noted that in the last three algorithms, an operator is added to the algorithm in order to improve the GSA performance.

The parameters of JADEEP algorithm are considered as the reference in this study [33]. As for The parameters of GPSO, ω was calculated at 0.9-0.4 and the acceleration coefficients were determined at 2 (C_1=C_2=2). In every modified version of GSA, the parameters were considered the same as that of the standard GSA [21]. Moreover, α was determined at 20 and G in these algorithms was formulated using Equation 16.

$$G = G_0 \exp(-\alpha \frac{t}{t_{max}}) \qquad (۱۶)$$

where G_0 is equal to 100, t is time, and t_{max} is the maximum number of iterations in the algorithm. The parameter θ is equal to 100 and the parameter ρ was determined at 10^{-16} in the D-GSA. In the BlackHole-GSA, the number of light objects was determined at N/5, where N is the total number of objects in the algorithm. As for the C-GSA, the parameters were considered the same as the parameters in a previously conducted study [36].

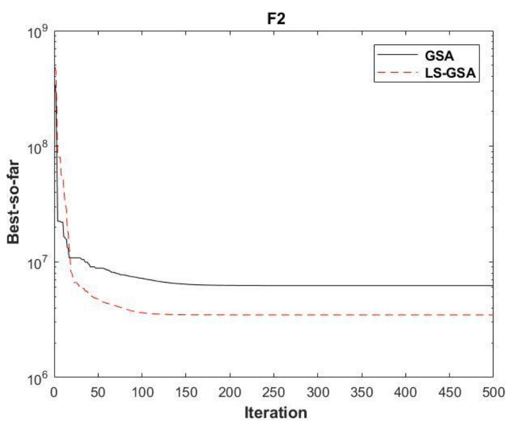
Table 1 shows the obtained experimental results using the benchmark functions (CEC). Furthermore, these results were assessed after 1e+5 fitness evaluations with a dimension of 50 (n=50). Each of these algorithms determines 51 independent iterations using a test function. The median error of these iterations was computed and reported in Table 1. The bold numbers and values in this table demonstrate the optimum solution and algorithm to solve each of the test functions.

As shown in Table 1, our proposed algorithm has the best performance with respect to the test functions F_8, F_{12}, F_{13}, F_{16}, F_{17}, F_{22}, F_{23}, and F_{24}. JADEEP has the best performance for the test functions F_1, F_2, F_4, F_5, F_{11}, F_{14}, F_{21} and F_{28}. GSA can solve the problem with a higher level of performance in test functions F_1, F_{17}, F_{18} and F_{23}. Moreover, D-GSA has the best performance for the test function F_{20}. The best solution for the test functions F_3, F_7, F_9, F_{10}, F_{15}, F_{25}, F_{26} and F_{27} can be achieved using BH-GSA. Finally, C-GSA can provide the best solutions for the test functions F_6 and F_{19}.

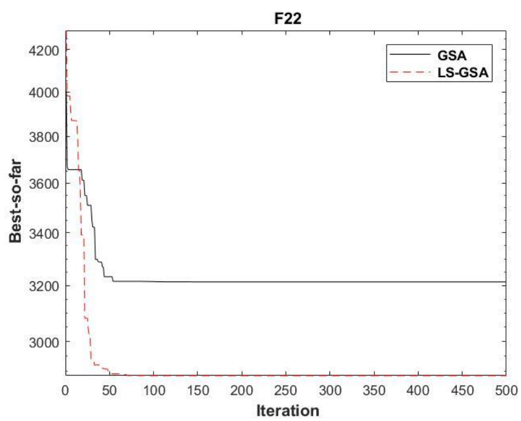
Figures 4.a. and 4.b. show the performance comparison of the proposed method for functions F_2 and F_{22}. The obtained results indicate that our proposed method, the improved GSA using linear scaling method, outperforms other standard optimization algorithms and state-of-the-art meta-heuristic search algorithms, particularly in the area of multimodal functions. These types of test function have numerous local optimum, therefore, they tend to be difficult and complex in order to be solved by optimization methods. The proposed method has a better performance with respect to these types of test and complex functions since it uses sigma scaling for the mass calculation. Hence, at the beginning of the proposed method, the value of these masses stays close to each other and consequently, the algorithm can fully explore the feasible search area. As the algorithm reaches toward the end, sigma scaling method provides heavier masses for reaching better solutions. Thus, the algorithm converges to the best solution. It is abundantly clear that our proposed method can control its abilities, such as exploration and exploitation using linear scaling. Moreover, the proposed method avoids local optima trapping due to its high exploration ability at the beginning of the algorithm. This method has a decent chance of

Table 1. Optimization results of the test functions.

	GPSO	*JADEEP*	*GSA*	*D-GSA*	*BH-GSA*	*C-GSA*	*LS-GSA*
F1	5.29E+03	**0.00E+00**	**0.00E+00**	4.50E-01	5.35E-14	1.42E-12	2.36E-15
F2	8.34E+07	**5.43E+03**	1.88E+06	6.78E+06	1.73E+06	2.09E+06	2.54E+05
F3	9.81E+10	6.19E+06	1.27E+08	4.97E+08	**1.39E+05**	1.37E+08	5.31E+08
F4	1.58E+04	**5.00E+03**	1.75E+04	1.70E+04	1.49E+04	1.88E+04	6.96E+03
F5	1.59E+03	**0.00E+00**	5.74E-05	2.79E+01	7.09E-05	5.97E-05	4.68E-05
F6	4.88E+02	9.09E-01	4.97E+01	6.90E+01	7.09E-05	**5.97E-05**	1.28E+01
F7	1.63E+02	4.67E+00	2.17E+01	2.86E+01	**1.23E+00**	1.83E+01	4.74E+01
F8	2.12E+01	2.09E+01	2.04E+01	2.04E+01	2.04E+01	2.10E+01	**2.00E+01**
F9	4.43E+01	2.69E+01	4.14E+00	4.71E+00	**1.63E+00**	4.16E+00	4.64E+00
F10	1.45E+03	3.75 E-02	1.03E-02	1.38E+00	**7.25E-04**	6.62E-03	1.58E-02
F11	1.56E+02	**0.00E+00**	2.53E+01	2.60E+01	5.17E+00	2.60E+01	2.76E+01
F12	3.73E+02	2.06E+01	2.40E+01	2.45E+01	3.51E+00	2.30E+01	**2.02E+00**
F13	5.87E+02	4.16E+01	4.46E+01	4.47E+01	6.57E+02	4.70E+01	**2.28E+01**
F14	2.59E+03	**4.39E-02**	8.99E+02	8.42E+02	3.13E+02	8.82E+02	1.28E+03
F15	7.76E+03	3.20E+03	4.91E+02	4.56E+02	**2.93E+02**	4.89E+02	3.92E+02
F16	2.09E+00	1.75E+00	1.56E-02	1.14E+00	2.07E-02	1.49E-02	**9.22E-03**
F17	3.46E+02	3.04E+01	**1.28E+01**	2.70E+01	1.32E+01	1.30E+01	**1.28E+01**
F18	3.45E+02	7.31E+01	**1.28E+01**	3.53E+01	1.38E+01	1.35E+01	1.32E+01
F19	4.36E+04	1.43E+00	1.22E+00	1.63E+00	1.37E+00	**1.14E+00**	1.78E+00
F20	2.22E+01	1.01E+01	4.08E+00	**4.00E+00**	4.02E+00	4.70E+00	7.88E+00
F21	9.33E+02	**2.98E+02**	4.00E+02	4.00E+02	4.00E+02	4.00E+02	4.00E+02
F22	4.25E+03	1.93E+03	1.93E+03	2.02E+03	4.22E+02	1.98E+03	**1.86E+03**
F23	1.06E+04	3.25E+03	1.28E+03	1.28E+03	4.63E+02	1.33E+03	**1.28E+02**
F24	3.37E+02	2.10E+02	2.20E+02	2.27E+02	2.07E+02	2.24E+02	**2.06E+02**
F25	4.81E+02	2.63E+02	2.15E+02	2.15E+02	**2.01E+02**	2.15E+02	3.34E+02
F26	4.17E+02	2.09E+02	3.25E+02	2.83E+02	**1.42E+02**	3.82E+02	5.28E+02
F27	1.68E+03	5.34E+02	4.00E+02	4.01E+02	**3.59E+02**	4.00E+02	4.56E+02
F28	4.33E+03	**3.00E+02**	6.46E+02	6.67E+02	3.14E+02	6.38E+02	8.16E+02



(a)



(b)

Figs 4. The comparison of performance of the proposed method and GSA on F_2 and F_22.

convergence due to its high exploitation ability at the end of the algorithm.

5.2 Performance Comparison

In this section, a two-sample t-test is used to analyze the results. The two-sample t-test is one of the most commonly used surveys [37]. It is routinely applied to investigate whether the mean difference between the two groups is indeed significant or can merely be associated with random chance.

Table 2 shows the statistical analysis and assessment of the two-sample t-test for test functions which were able to calculate a confidence interval. The hypothesis test of the difference between the two population means was determined and reported in table 2 while the standard deviations of the population were unknown and samples were generated independently from each other. Samples for this test were the output of 50 independent iterations of GSA and LS-GSA using the previous benchmark test functions.

In this two-sample t-test, null hypothesis demonstrates that the data in two samples which came from independent random samples of a normal distribution have equal means. In this test, the alternative hypothesis states the samples data have unequal means. In table 2, T-Test column revealed that the test decision for the null hypothesis. The value of this column is considered one provided that the test rejects the null hypothesis with a 5% significance level, and 0 otherwise. The P-Value column demonstrates the probability of observing a test statistic as or more extreme than the observed value under the null hypothesis. The P-value column is defined over the interval of [0, 1]. The data in this two-sample test came from normal distributions with equal or unequal unknown variances. The variance of these data was determined by F-test and was reported in Table 2. The results of this analysis on test functions showed that our proposed method has a better performance compared to the GSA algorithm for most of the test functions. Thus, linear scaling can improve the performance of GSA by controlling the exploitation and exploration abilities.

Table 2. Statistical analysis on test functions.

Function Number	*Variance Type*	*T-Test*	*P-Value*
F1	**equal**	**1**	**3.7108e-11**
F2	**unequal**	**1**	**6.1257e-21**
F3	**unequal**	**1**	**5.0051e-15**
F4	**equal**	**0**	**0.8526**
F5	**unequal**	**1**	**3.1079e-19**
F6	**unequal**	**1**	**5.7512e-13**
F7	**equal**	**0**	**0.3084**
F8	**equal**	**0**	**0.6903**
F9	**equal**	**1**	**2.0036e-05**
F10	**unequal**	**1**	**9.1291e-08**
F11	**equal**	**1**	**6.1725e-06**
F12	**equal**	**1**	**2.9716e-07**
F13	**equal**	**1**	**0.0026**
F14	**equal**	**1**	**0.0125**
F15	**equal**	**1**	**0.0096**
F16	**unequal**	**1**	**0.0030**
F17	**equal**	**0**	**0.9637**
F18	**equal**	**0**	**0.7260**
F19	**equal**	**1**	**0.0106**
F20	**unequal**	**0**	**1**
F21	**equal**	**1**	**0.0095**
F22	**equal**	**1**	**0.1618**
F23	**equal**	**0**	**0.7268**
F24	**unequal**	**1**	**0.0135**
F25	**equal**	**1**	**0.0136**
F26	**equal**	**1**	**0.0133**
F27	**unequal**	**1**	**0.0658**
F28	**equal**	**1**	**2.6912e-09**

5.3 The K-of-N Lifetime Problem

In this subsection, the proposed method was used to find the optimum location of the base station in the K-of-N lifetime problem in a two-tiered WSNs architecture. This simulation was carried out using C language in an Intel PC with a 2 GHz processor, 1 GB main memory, and operating on Microsoft Windows XP. In this simulation, the target area was a 1000 m by 1000 m space, serves as a two-dimensional real-number space. The initial energy was limited between 100000000 and 999999999 and the data transmission rate varied from 0 to 1000. The number of application nodes in the network was determined at 50 and the properties of each application node, such as data transmission rate, initial energy, and its location were randomly determined. Moreover, the distance-independent parameter was set to 0 ($a_j1=0$), and the distance-dependent parameter was set to 1 ($a_j2=1$) for each AN. In addition, the maximum number of active ANs was set to 40 (K=40). The number of agents in the proposed method was set to 15 and the maximum number of iterations was set to 50. Finally, other parameters of our proposed method and PSO algorithm were determined in the same way as the previous section.

The results of this simulation were obtained as follows. Ten independent two-tiered WSN architectures were randomly generated and 50 iterations of each method were evaluated on these networks. The mean lifetime and termination of these iterations were computed and reported in Table 3 and Table 4 [19].

Table 3 shows the lifetime comparison of the proposed method with other popular approaches, such as the PSO-based method and the exhaustive grid search method having different grid size number for the K-of-N lifetime problem in a two-tiered WSN architecture [19]. This table confirms that the proposed method has, in fact, the best performance

Table 3. The lifetime comparison of the approaches

Method	Lifetime
The proposed algorithm	212.4415
The PSO algorithm	212.4404
The exhaustive grid search (grid size =1)	212.0781
The exhaustive grid search (grid size =0.1)	212.4158
The exhaustive grid search (grid size =0.01)	212.4379

Table 4. The execution time comparison with respect to the implemented method

Method	Time (sec.)
The proposed algorithm	0.22
The PSO algorithm	0.06
The exhaustive grid search (grid size =1)	36.563
The exhaustive grid search (grid size =0.1)	2480.718
The exhaustive grid search (grid size =0.01)	170871.8558

for finding the best location of the base station in this K-of-N lifetime problem.

The execution time comparison of the proposed method with the PSO-based approach and the exhaustive grid search approach having different grid size number is shown in Table 4 [19]. According to this table, the exhaustive grid search approaches are rather difficult and complex to solve with long execution runtime; on the other hand, the proposed method and the PSO-based approach have a relatively shorter execution time. The reason behind this short execution runtime is that the proposed method and PSO are random search algorithm. These algorithms use simple operations and functions to find a good solution for the problem in reasonable execution time.

The simulation results indicated that our proposed method which solves the K-of-N lifetime problem using an improved GSA has a higher level of performance with respect to other popular methods. The reason behind this performance and significant achievement can be associated with the notion that the proposed method searches the target area to find the best location of the base station. In this search algorithm, linear scaling method was used to control the exploitation and exploration abilities of the algorithm. Thus, the algorithm explores the entire feasible area at the initial iterations and then convergence to the best answer. Hence, the proposed method can solve this problem in a more efficient way compared to other approaches despite its simplicity in implementation.

6. Conclusion

In this research paper, the linear scaling method was used to introduce a new function for mass calculation in the gravitational search algorithm. It was indicated that this method could fully control the abilities of the search algorithm, such as exploration and exploitation. The results suggested that this novel search algorithm can improve the GSA performance compared to other state-of-the-art meta-heuristic search algorithms despite its simplicity in implementation. Then, this algorithm was employed to solve the K-of-N lifetime problem in a two-tiered WSNs architecture. In our proposed method, the improved GSA explores the target area to find the best location of the base station in order to enhance the network lifetime. The simulation results recommended that our proposed method has a better performance in comparison to other standard approaches to solving K-of-N lifetime problem.

Conflict of Interest: The authors declare that they have no conflict of interest.

References

[1] M.R.K. Aziz, K. Anwar, T. Matsumoto, Monitoring spot configuration of RSS-based factor graph geolocation technique in outdoor WSN environment, in: IEICE General Conference, 2015.

[2] M. Amiribesheli, A. Benmansour, A. Bouchachia, A review of smart homes in healthcare, Journal of Ambient Intelligence and Humanized Computing, 6(4) (2015) 495-517.

[3] A.B. Noel, A. Abdaoui, T. Elfouly, M.H. Ahmed, A. Badawy, M.S. Shehata, Structural health monitoring using wireless sensor networks: A comprehensive survey, IEEE Communications Surveys & Tutorials, 19(3) (2017) 1403-1423.

[4] A. Jothimani, A.S. Edward, K.M. Gowthem, R. Karthikeyan, Implementation of smart sensor interface network for water quality monitoring in industry using iot, Indian Journal of Science and Technology, 10(6) (2017).

[5] B. Prabhu, M. Pradeep, E. Gajendran, Military Applications of Wireless Sensor Network System, (2017).

[6] T.R. Sheltami, S. Khan, E.M. Shakshuki, M.K. Menshawi, Continuous objects detection and tracking in wireless sensor networks, Journal of Ambient Intelligence and Humanized Computing, 7(4) (2016) 489-508.

[7] T.R. Sheltami, A. Bala, E.M. Shakshuki, Wireless sensor networks for leak detection in pipelines: a survey, Journal of Ambient Intelligence and Humanized Computing, 7(3) (2016) 347-356.

[8] O. Ojuroye, R. Torah, S. Beeby, A. Wilde, Smart textiles for smart home control and enriching future wireless sensor network data, in: Sensors for Everyday Life, Springer, 2017, pp. 159-183.

[9] H.Y. Shwe, P.H.J. Chong, WSN-based energy-efficient data communication protocol for smart green building environment, in: Telecommunications Energy Conference (INTELEC), 2015 IEEE International, IEEE, 2015, pp. 1-5.

[10] W.R. Heinzelman, A. Chandrakasan, H. Balakrishnan, Energy-efficient communication protocol for wireless microsensor networks, in: System sciences, 2000. Proceedings of the 33rd annual Hawaii international conference on, IEEE, 2000, pp. 10 pp. vol. 12.

[11] S.D. Muruganathan, D.C. Ma, R.I. Bhasin, A.O. Fapojuwo, A centralized energy-efficient routing protocol for wireless sensor networks, IEEE Communications Magazine, 43(3) (2005) S8-13.

[12] D. Niculescu, B. Nath, Ad hoc positioning system (APS) using AOA, in: INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies, Ieee, 2003, pp. 1734-1743.

[13] C. Sharma, V. Pattanik, Survey Paper of Energy Efficient Data Aggregation Protocol in Wireless Sensor Network, International Journal of Computer Applications, 150(8) (2016).

[14] K. Vijayan, A. Raaza, A novel cluster arrangement energy efficient routing protocol for wireless sensor networks,

Indian Journal of science and Technology, 9(2) (2016).

[15] G. Kannan, T.S.R. Raja, Energy efficient distributed cluster head scheduling scheme for two tiered wireless sensor network, Egyptian Informatics Journal, 16(2) (2015) 167-174.

[16] J. Pan, L. Cai, Y.T. Hou, Y. Shi, S.X. Shen, Optimal base-station locations in two-tiered wireless sensor networks, IEEE Transactions on Mobile Computing, 4(5) (2005) 458-473.

[17] T. Shankar, S. Shanmugavel, A. Rajesh, Hybrid HSA and PSO algorithm for energy efficient cluster head selection in wireless sensor networks, Swarm and Evolutionary Computation, 30 (2016) 1-10.

[18] X. Yuan, M. Elhoseny, H.K. El-Minir, A.M. Riad, A genetic algorithm-based, dynamic clustering method towards improved WSN longevity, Journal of Network and Systems Management, 25(1) (2017) 21-46.

[19] T.-P. Hong, G.-N. Shiu, Solving the K-of-N Lifetime Problem by PSO, International Journal of Engineering, Science and Technology, 1(1) (2009) 136-147.

[20] M. Zain-Ul-Abidin, H. Maqsood, U. Qasim, Z.A. Khan, N. Javaid, Improved genetic algorithm based energy efficient routing in two-tiered wireless sensor networks, in: Network-Based Information Systems (NBiS), 2016 19th International Conference on, IEEE, 2016, pp. 382-386.

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

[22] E. Rashedi, H. Nezamabadi-Pour, S. Saryazdi, BGSA: binary gravitational search algorithm, Natural Computing, 9(3) (2010) 727-745.

[23] S. Mirjalili, S.Z.M. Hashim, H.M. Sardroudi, Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm, Applied Mathematics and Computation, 218(22) (2012) 11125-11137.

[24] C. Purcaru, R.-E. Precup, D. Iercan, L.-O. Fedorovici, R.-C. David, F. Dragan, Optimal robot path planning using gravitational search algorithm, Int. J. Artif. Intell, 10 (2013) 1-20.

[25] J.R. Parvin, C. Vasanthanayaki, Gravitational search algorithm based mobile aggregator sink nodes for energy efficient wireless sensor networks, in: Circuits, Power and Computing Technologies (ICCPCT), 2013 International Conference on, IEEE, 2013, pp. 1052-1058.

[26] M.K. Rafsanjani, M.B. Dowlatshahi, Using gravitational search algorithm for finding near-optimal base station location in two-tiered WSNs, International Journal of Machine Learning and Computing, 2(4) (2012) 377.

[27] W. Zhao, Adaptive image enhancement based on gravitational search algorithm, Procedia Engineering, 15 (2011) 3288-3292.

[28] B. González, F. Valdez, P. Melin, G. Prado-Arechiga, Fuzzy logic in the gravitational search algorithm for the optimization of modular neural networks in pattern recognition, Expert Systems with Applications, 42(14) (2015) 5839-5847.

[29] M. Behrang, E. Assareh, M. Ghalambaz, M. Assari, A. Noghrehabadi, Forecasting future oil demand in Iran using GSA (Gravitational Search Algorithm), Energy, 36(9) (2011) 5649-5654.

[30] X. Li, K. Tang, M.N. Omidvar, Z. Yang, K. Qin, H. China, Benchmark functions for the CEC 2013 special session and competition on large-scale global optimization, gene, 7(33) (2013) 8.

[31] X. Li, A. Engelbrecht, M.G. Epitropakis, Benchmark functions for CEC'2013 special session and competition on niching methods for multimodal function optimization, RMIT University, Evolutionary Computation and Machine Learning Group, Australia, Tech. Rep, (2013).

[32] J. Liang, B. Qu, P. Suganthan, A.G. Hernández-Díaz, Problem definitions and evaluation criteria for the CEC 2013 special session on real-parameter optimization, Computational Intelligence Laboratory, Zhengzhou University, Zhengzhou, China and Nanyang Technological University, Singapore, Technical Report, 201212 (2013) 3-18.

[33] J. Zhang, A.C. Sanderson, JADE: adaptive differential evolution with optional external archive, IEEE Transactions on evolutionary computation, 13(5) (2009) 945-958.

[34] M.M. Noel, A new gradient based particle swarm optimization algorithm for accurate computation of global minimum, Applied Soft Computing, 12(1) (2012) 353-359.

[35] S. Sarafrazi, H. Nezamabadi-Pour, S. Saryazdi, Disruption: a new operator in gravitational search algorithm, Scientia Iranica, 18(3) (2011) 539-548.

[36] M. Shams, E. Rashedi, A. Hakimi, Clustered-gravitational search algorithm and its application in parameter optimization of a low noise amplifier, Applied Mathematics and Computation, 258 (2015) 436-453.

[37] N. Cressie, H. Whitford, How to use the two sample t-test, Biometrical Journal, 28(2) (1986) 131-148.

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