Optimal Base Station Locations in Heterogeneous Wireless Sensor Network Based on Hybrid Particle Swarm Optimization with Bat Algorithm

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Abstract. In this paper, a hybrid Particle Swarm Optimization with Bat Algorithm (PBA) for applying to the base-station locations optimization in the heterogeneous wireless sensor networks (WSNs) is proposed. In this work, the several worst individuals of particles in Particle Swarm Optimization (PSO) will be replaced with the best individuals in Bat Algorithm (BA) after running some fixed iterations, and on the contrary, the poorer individuals of BA will be replaced with the finest particles of PSO. The communicating strategy provides the information flow for the particles in PSO to communicate with the bats in BA. Six benchmark functions are used to test the behavior of the convergence, the accuracy, and the speed of the approached method. The results show that the proposed scheme increases more the convergence and the accuracy than BA and PSO up to 3% and 47% respectively. In addition, compared with PSO and BA methods, the proposed PBA method can provide the longest the network lifetime of the heterogeneous WSNs.

Keywords: Hybrid Particle Swarm Optimization with Bat Algorithm, Particle Swarm Optimization Algorithm, Bat Algorithm Optimizations, Swarm Intelligence, Wireless Sensor Networks.

1 Introduction

Computational intelligence algorithms have been used to solve optimization problems in engineering, financial, and management fields. For example, genetic algorithms (GA) have been used successfully in engineering, financial, and security [1-3]. Particle swarm optimization (PSO) techniques have been employed to forecast the exchange rates, segment images, optimize multiple interference cancellations [4-7], construct the portfolios of stock, and segment color images based on human perception [3, 8, 9]. Differential evolution algorithm (DE) techniques have been applied to optimize the radio network design and measures networks target coverage in three-dimensional heterogeneous sensor [10, 11]. Ant colony optimization (ACO) techniques have been utilized to solve the routing problem of networks and secure watermarking [12, 13]. Artificial bee colony (ABC) and Interactive Artificial Bee Colony have been used to solve the numerical problems, support the passive continuous authentication systems and optimize the topology control problems [14-16]. Cat swarm optimization (CSO) techniques have been used to solve the aircraft schedule[17], the lot-streaming flow shop scheduling problem [18] and discover proper positions for information hiding [19], respectively. In addition, bat algorithm (BA) is used for engineering design [20] and classifications[21].

Communication between two algorithms is to take the advantage of the strength points of each type of algorithms. The parallel processing plays an important role for the efficient and effective computations of function optimization. The idea of this paper is based on communication strategies in parallel processing for swarm intelligent algorithms. They only exchange information between populations when the communication strategy is triggered. The existing methods of these fields had been introduced such as: Ant colony system with communication strategies [22], Parallel particle swarm optimization algorithm with communication strategies [23], Parallel cat swarm optimization [24], Island-model genetic algorithm [25], and Parallel genetic algorithm [26]. The parallelized structure of artificial agents increases the accuracy and extends the global search capacity than the original structure.

In this paper, the concepts of parallel processing and communication strategy are applied to hybrid Particle Swarm Optimization with Bat algorithm (PBA) is proposed. In the new proposed method of PBA, the several poorer individuals in PSO will be replaced with the best bats in BA algorithm after running some fixed iterations and on the contrary, the poorer bats of BA will be replaced with the best particles of PSO. The selected benchmark functions are used to test the behavior of convergence, the accuracy, and the speed of the proposed PBA method. The experimental results show that the proposed method increases higher the accuracy in comparing with the popular algorithms in literature such as PSO and BA.

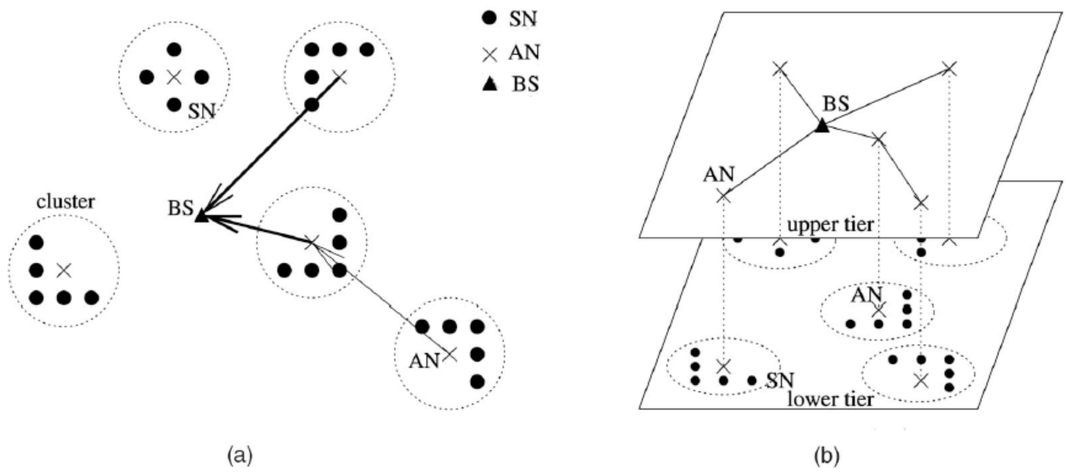

Fig. 1. Example of heterogeneous architecture of WSNs [27] (a) Physical view, (b) Logical view (SN- Sensor Node, AN-Application Node and BS-Base station)

Moreover, an emerging and promising technology, wireless sensor network (WNS) consists of spatially distributed sensor nodes to collect important information in the target environment. It has been widely used in variety of fields such as Health care, the Internet of things, Traffic control, Home automation and Battlefield surveillance and etc. [28-32]. However, the sensor nodes are limited in computation capability and storage capacity of computing unit, in communication range and radio quality of communication unit, in sensing coverage and accuracy of sensing unit, and in available energy of power units. Efficient utilization of these scarce resources is always the driving factor of every provided solution for WSN [31, 33]. A fundamental problem in WSNs is to maximize the system lifetime under some given constraints.

The location of the base-station (BS) is an impacting effective factor to contribute the saving and balancing power consumption of the application nodes (ANs) in heterogeneous WSNs. Figure 1 is the example of Example of heterogeneous architecture of WSNs [27]. The ANs near the base station die out earlier, because they will be subject to heavier relay traffic load than those ANs farther away from the base station [34]. The optimal BS location is how to determine relative position of BS with ANs for distributing balanced energy consumption among ANs while remain the quality of service network.

The new proposed PBA [35] method would be applied to maximize the heterogeneous WSNs lifetime through the BS location optimization. The lifetime of networks is defined as categories: First, the lifetime is minimization of any alive of individual AN. Second, the lifetime is the radio of the covered area over the originally covered area is smaller than percentage beta. A fitness function based on energy consumption per unit time is also applied in PBA to obtain an approximation of true Pareto front.

The rest of this paper is organized as follows: the brief review of PSO and BA are given in session 2 and 3 respectively; the statement problem of BS locations in WSNs is reviewed in session 4; the analysis and design for the PBA is presented in session 5; a series of experimental results and the comparison between primary PSO, original BA and PBA are discussed in session 6; the application of PBA for solving the topology control scheme is presented in session 7; finally, the conclusion is summarized in session 8.

2 Heterogeneous Application Node Model for WSNs

A fundamental problem in wireless sensor networks is to maximize the system lifetime under some given constraint [34]. Heterogeneous WSNs was found in two-tiered wireless sensor networks [27]. A two-tiered wireless sensor network (WSN) consists of a set of small sensor nodes (SN), a set of application nodes (AN) and at least one base station (BS). The ANs and SNs form clusters, and in each cluster there are many SNs and one AN. A small sensor, once triggered by the internal timer or some external signals, starts to capture and encode the environmental phenomena (such as temperature, moisture, motion measure, etc) and broadcast the data directly to all ANs within its transmission range and to certain ANs via the relay of some other neighboring sensors. When receiving the raw data from SNs from its cluster, an AN might create an application specific local-view for the whole cluster by exploring some correlations among the data sent by different SNs. In the meanwhile, some data fusion can be conducted by ANs to alleviate the redundancy in the raw data sent by SNs. After an AN creates a local-view of the data, it then forwards the information to a BS that generates a comprehensive global view for the entire WSN. Notice that here an AN can communicate directly with a BS, or optionally, ANs can be involved in inter-AN relaying if such activities are needed and applicable.

The heterogeneous ANs might have different data transmission rates. If a single SN ran out of energy, its corresponding AN might still have the capability to collect enough information. However, if an AN ran out of energy, the information in its coverage range would be completely lost, which was dangerous to the whole system. Let *d* be the Euclidean distance from an AN to a BS, and *r* be the data transmission rate. The energy consumption per unit time can be calculated as following:

$$p(r,d) = r(\alpha_1 + \alpha_2 d^n) \tag{1}$$

where α_1 is a distance-independent parameter and α_2 is a distance-dependent parameter. The energy consumption thus relates to Euclidean distances and data transmission rates. It is assumed each AN has the same α_1, α_2. The lifetime of AN can be calculated as following:

$$l = \frac{e}{p(r,d)} \tag{2}$$

where *l* is lifetime of application node, *e* is initial energy of application node. For homogenous ANs, the data transmission rate is constant so the center of the minimal circle covering all the ANs is the optimal BS location (with the maximum lifetime). For heterogeneous ANs, the data transmission rates are different. The average rate over a period of time is given as:

$$r = \frac{\int_{T_0}^{T+T_0} r_i(t)}{T} \tag{3}$$

where $r_i(t)$ is a function over the time *t*, *T* is a period of time, e.g., one hour or one day or one week, most often it is a constant. The optimal BS location is actually determined by a few critical ANs that run out of energy first. The network lifetime is equivalent to maximize ($\min\{l_i\}$).

$$L = Max(\min\{l_i = e_i/(r_i(\alpha_1 + \alpha_2 {d_i}^n)\}) \tag{4}$$

$$d_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \tag{5}$$

where b= (x_0,y_0) is the BS station.

3 Particle Swarm Optimization

Particle swarm optimization (PSO) is a heuristic global optimization algorithm, based on the research of bird and fish flock in movement behavior [6, 7, 36]. The particles are randomly initialized and freely fly across the multi-dimensional search space. While they are flying, its velocity and position are updated based on its own best experience. The updating policy will cause the particle swarm to move toward a region with a higher object value. The position of each particle is equivalent to a candidate solution of a problem. The particle moves according to an adjusted velocity, which is based on that particle's experience and the experience of its companions. The original particle swarm optimization algorithm can be expressed as follows:

$$V_i^{t+1} = V_i^t + C_1 \times r_1(P_i^t - X_i^t) + C_2 \times r_2(G^t - X_i^t) \tag{6}$$

where V_i^t is the velocity of the *i-th* particle at the *t-th* iteration, C_1 and C_2 are factors of the speed control, r_1 and r_2 are random variables such that $0 \le r_1$, $r_2 \le 1$, P_i^t is the best previous position of the *i-th* particle at the *t-th* iteration, G_t is the *best* position amongst all the particles, from the first iteration to the *t-th* iteration, and X_i^t is the *i-th* particle for the *t-th* iteration.

$$X_i^{t+1} = X_i^t + V_i^{t+1},\ \ i = 0,1,..N-1 \tag{7}$$

where *N* is the particle size, $-V_{\max} \le {V^{t+1}}_i \le V_{\max}$ ($V_{\max}$ is the maximum velocity).

A modified version of the particle swarm optimizer [7] and an adaption using the inertia weight which is a parameter for controlling the dynamics of flying of the modified particle swarm [37], have also been presented. The latter version of the modified particle swarm optimizer can be expressed as equation (8).

$$V_i^{t+1} = W^t \times V_i^t + C_1 \times r_1(P_i^t - X_i^t) + C_2 \times r_2(G^t - X_i^t) \quad \textbf{(8)}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1}, \quad i = 0,1,..N-1 \quad \textbf{(9)}$$

where W^t is the inertia weight at the *t-th* iteration.

4 Bat Algorithm

Bat Algorithm (BA) was proposed based on swarm intelligence and the inspiration from observing the bats [38]. BA simulated parts of the echolocation characteristics of the micro-bat in the simplicity way. Three major characteristics of the micro-bat are employed to construct the basic structure of BA. The idealized rules in this method are listed as follows: The echolocation to detect the prey is utilized for all bats, but not all species of the bat do the same thing. However, the micro-bat, one of species of the bat is a famous example of extensively using the echolocation. Hence, the first characteristic is the echolocation behavior. The second characteristic is the frequency. The frequency is sent by the micro-bat with frequency f and with a variable wavelength λ. The loudness A_0 is used to search for prey. The other characteristic of them are listed as follows:

1. Bats fly randomly with velocity v_i at position x_i. They can adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r from 0 to1, depending on the proximity of their target;
2. There are many ways to adjust the loudness. For simplicity, the loudness is assumed to be varied from a positive large A_0 to a minimum constant value, which is denoted by Amin.

The movement of the virtual bat is simulated by equation (9) – equation (11):

$$f_i = f_{min} + (f_{max} - f_{min}) * \beta \quad \textbf{(9)}$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_{best}) * f_i \quad \textbf{(10)}$$

$$x_i^t = x_i^{t-1} + \mathrm{v}_\mathrm{i}^\mathrm{t} \quad \textbf{(11)}$$

where f is the frequency used by the bat seeking for its prey, f_{min} and f_{max}, represent the minimum and maximum value, respectively, x_i denotes the location of the *i-th* bat in the solution space, v_i represents the velocity of the bat, t indicates the current iteration, β is a random vector, which is drawn from a uniform distribution, and $\beta \in [0, 1]$, and x_{best} indicates the global near best solution found so far over the whole population.

In addition, the rate of the pulse emission from the bat is also taken to be one of the roles in the process. The micro-bat emits the echo and adjusts the wavelength depending on the proximity of their target. The pulse emission rate is denoted by the symbol r_i, and $r_i \in [0,1]$, where the suffix i indicates the *i-th* bat. In every iteration, a random number is generated and is compared with r_i. If the random number is greater than r_i, a local search strategy, namely, random walk, is detonated. A new solution for the bat is generated by equation (12):

$$x_{new} = x_{old} + \varepsilon A^t \quad \textbf{(12)}$$

where ε is a random number and $\varepsilon \in [-1,1]$, and the average loudness of all bats is represented at the current time step t. After updating the positions of the bats, the loudness A_i and the pulse emission rate r_i are also updated only whenever the global near best solution is updated and the random generated number is smaller than A_i. The update of A_i and r_i are operated by equation (13) and equation (14):

$$A_i^{t+1} = \alpha A_i^t \quad \textbf{(13)}$$

$$r_i^{t+1} = r_i^0[1 - e^{-\gamma t}] \quad \textbf{(14)}$$

where α and γ are constants. In Yang's experiments, $\alpha = \gamma = 0.9$ is used for the simplicity.

The process of BA is depicted as follows:

Step 1. Initialize the bat population, the pulse rates, the loudness, and define the pulse frequency

Step 2. Update the velocities to update the location of the bats, and decide whether detonate the random walk process.

Step 3. Rank the bats according to their fitness value, find the current best solution found so far, and then update the loudness and the emission rate.

Step 4. Check the termination condition to decide whether go back to step 2 or end the process and output the result.

5. The Proposed Hybrid PSO with BA

Hybrid optimization algorithm is structured by communication strategies between two algorithms in this paper. This idea is based on replacing the weaker individuals according to fitness evaluation of one algorithm with stronger individuals from other algorithm in parallel processing for swarm intelligent algorithms. Several groups in a parallel structure of hybrid algorithm are created by dividing the population into subpopulations. Each of the subpopulation evolves independently in regular iterations. They only exchange information between populations when the communication strategy is triggered. It results in taking advantage of the individual strengths of each type of algorithm. The replacement of weaker individuals in running algorithms will be achieved so on to get the benefit of the cooperation. PBA is designed based on original PSO and Bat algorithm. Each algorithm evolves by optimization independently, i.e. the PSO has its own individuals and the better solution to replace the worst artificial bats of BA. In contrast, the better artificial bats of BA are to replace the poorer individuals of PSO after running some fixed iterations. The total iteration contains R times of communication, where $R = \{R_1, 2R_1, 3R_1, ...\}$. Let N be the number of population of PBA, and N_1, N_2 be the number of population of PSO and BA respectively, where N_1 and N_2 are set to be $N/2$. If $t \cap R \neq \varphi$, k agents with the top k fitness in N_1 will be copied to N_2 to replace the same number of individuals with the worst fitness, where t denotes the current iteration count, R_1 and k are the predefined constants.

The diagram of the PBA with communication strategy is shown in Figure 2.

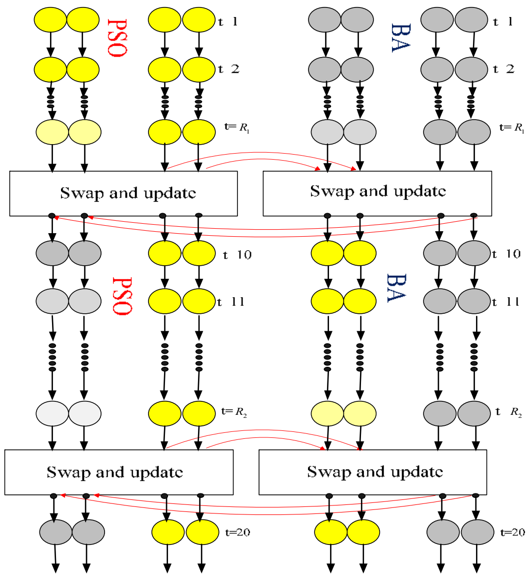

Fig. 1. The diagram of PBA with a communication strategy

1. **Initialization:** Generate populations for both PSO and BA. Each population is initialized by BA or by PSO independently. Defined the iteration set R for executing the communication strategy. The N_1, N_2 are the number of particles and artificial agents in solutions S_{ij}^T and X_{ij}^T for populations of PSO and BA respectively, $i = 0, 1, \ldots, N_1 - 1$, $j = 0, 1,..D$. D is dimension of solutions and t is current iteration number. Set $t = 1$.
2. **Evaluation:** Evaluate the value of $f_1(S_{ij}^T)$, $f_2(X_{ij}^T)$ for both PSO and BA in each population. The evolvement of the populations is executed independently by both PSO and BA.
3. **Update:** Update the velocity and the positions of PSO using equation (5), and (6). Update the location and velocity of Bat in the best fitness value, which are found by the bat using equations (10), (11).
4. **Communication Strategy:** Migrate the best artificial bats among all the individuals of BA's population, copy k bats with the top k fitness in N_1 replace the poorer particles in N_2 of PSO's population and update for each population every R_1 iterations.
5. **Termination:** Repeat step 2 to step 5 until the predefined value of the function is achieved or the maximum number of iterations has been reached. Record the best value of the function $f(S^t)$ and the best particle position among all the particles S^t. Record the best value of the function $f(X^t)$ and the best location among all the bats X^t.

6 Experimental Results

This section presents simulation results and compares the PBA with the PSO, and the BA, both in terms of solution quality, convergence capability, the accuracy and the speed running. Six benchmark functions are used to test the accuracy and the convergence of PBA. All the benchmark functions for experimenting are averaged over different random seeds with 10 runs. Let $S = \{s_1, s_2, ..., s_m\}$, $X = \{x_1, x_2, ..., x_m\}$ be the m-dimensional real-value vectors for PSO and BA respectively. The benchmark functions are Ackley, Griewank, Quadric, Rastrigin, Rosenbrock and Spherical. The equation numbers (15) to (20). The goal of the optimization is to minimize the outcome for all benchmarks. The population size of PBA, primary PSO and original BA are set to 20 (*N=20*) for all the algorithms in the experiments. The detail of parameter settings of PSO can be found in [39], and setting of BA can be found in [38].

$$f_1(x) = 20 + e - 20e^{-0.2\sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}}} - e^{\frac{\sum_{j=1}^{n}\cos(2\pi x_i)}{n}} \quad \textbf{(15)}$$

$$f_2(x) = 1 + \sum_{i=1}^{N} \frac{x_i^2}{4000} + \prod_{i=1}^{N} cos\frac{x_i}{\sqrt{i}} \quad \textbf{(16)}$$

$$f_3(x) = \sum_{i=1}^{n}\left(\sum_{k=1}^{i} x_i\right)^2 \quad \textbf{(17)}$$

$$f_4(x) = \sum_{i=1}^{N}[10 + x_i^2 - 10cos2\pi x_i] \quad \textbf{(18)}$$

$$f_5(x) = \sum_{i=1}^{n-1}(100(x_{i-1} - x_i^2)^2 + (1 - x_i)^2 \quad \textbf{(19)}$$

$$f_6(x) = \sum_{i=1}^{N} x_i^2 \quad \textbf{(20)}$$

The initial range and the total iteration number for all test functions are listed in Table1.

Table 1. The initial range and the total iteration of test standard functions.

Functions		Initial range $[x_{min}, x_{max}]$	Total iteration
Ackley	$f_1(x)$	[-100,100]	200
Griewangk	$f_2(x)$	[5.12,5.12]	200
Quadric	$f_3(x)$	[-100,100]	200
Rastrigin	$f_4(x)$	[-30,30]	200
Rosenbrock	$f_5(x)$	[-100,100]	200
Spherical	$f_6(x)$	[-100,100]	200

The optimization for all of these test functions is to minimize the outcome. The parameters setting for PBA with primary PSO side are the initial inertia weight $W = (0.9 - 07 * rand)$, coefficients of learning factors c_1=-2 and c_2=2 in PSO, the total population size N_1 = 10 and the dimension of the solution space *M = 10*, and with original BA side are the initial loudness $A_i^0 = 0.25$, pulse rate $r_i^0 = 0.5$ the total population size N_1 = 10 and the dimension of the solution space *M = 10*, frequency minimum f_{min} = *the lowest of initial range function* and frequency minimum f_{max} = *the highest of initial range function.* The proposed scheme is executed for 10 runs and each run contains 200 iterations. The final result is obtained by taking the average of the outcomes from all runs. These results also are compared with the primary PSO and original BA respectively.

Table 2 compares the quality of optimizing performance and time running for numerical problem optimization between PBA and PSO. It is clearly seen that, almost these cases of testing benchmark functions for PBA are better than PSO in terms of convergence and accuracy. It is special case with test function of Rosenbrock, $f_5(x)$ has the mean of value function minimum of total seeds of 10 runs is 1.02E+09 for PBA performance evaluation, but, for original PSO is 2.90E+09, reaches at 48% improvement of convergence. The average performance evaluation value of six benchmark functions is 1.70E+08 for PBA and 4.83E+08 for original PSO, gets at 47% improvement of accuracy. However, all benchmark functions for average time consuming of hybrid BA-BA are longer than that in original PSO, for the reasons, the hybrid algorithm must perform mutation and update operations.

Figure 2 shows the experimental results of six benchmark functions in running repeatedly same iteration of 200 in random seeds of 10 runs. It clearly can be seen that the most cases of curves of PBA (solid red line) are more convergent than those of PSO (doted blue line).

Table 2. The comparison between PBA and origianl PSO in terms of quality performance evaluation and speed

Function	Performance evaluation		Time running evaluation (seconds)	
	PSO	***Hybrid PSO-BA(PBA)***	***PSO***	***Hybrid PSO-BA(PBA)***
$f_1(x)$	1.96E+01	1.85E+01	0.079	0.134
$f_2(x)$	1.92E+00	1.81E+00	0.086	0.139
$f_3(x)$	4.46E+03	2.62E+03	0.109	0.230
$f_4(x)$	1.23E+02	1.11E+02	0.080	0.148
$f_5(x)$	2.90E+09	1.02E+09	0.081	0.159
$f_6(x)$	1.62E+04	7.13E+03	0.064	0.121
Average value	**4.83E+08**	**1.70E+08**	**0.33**	**0.49**

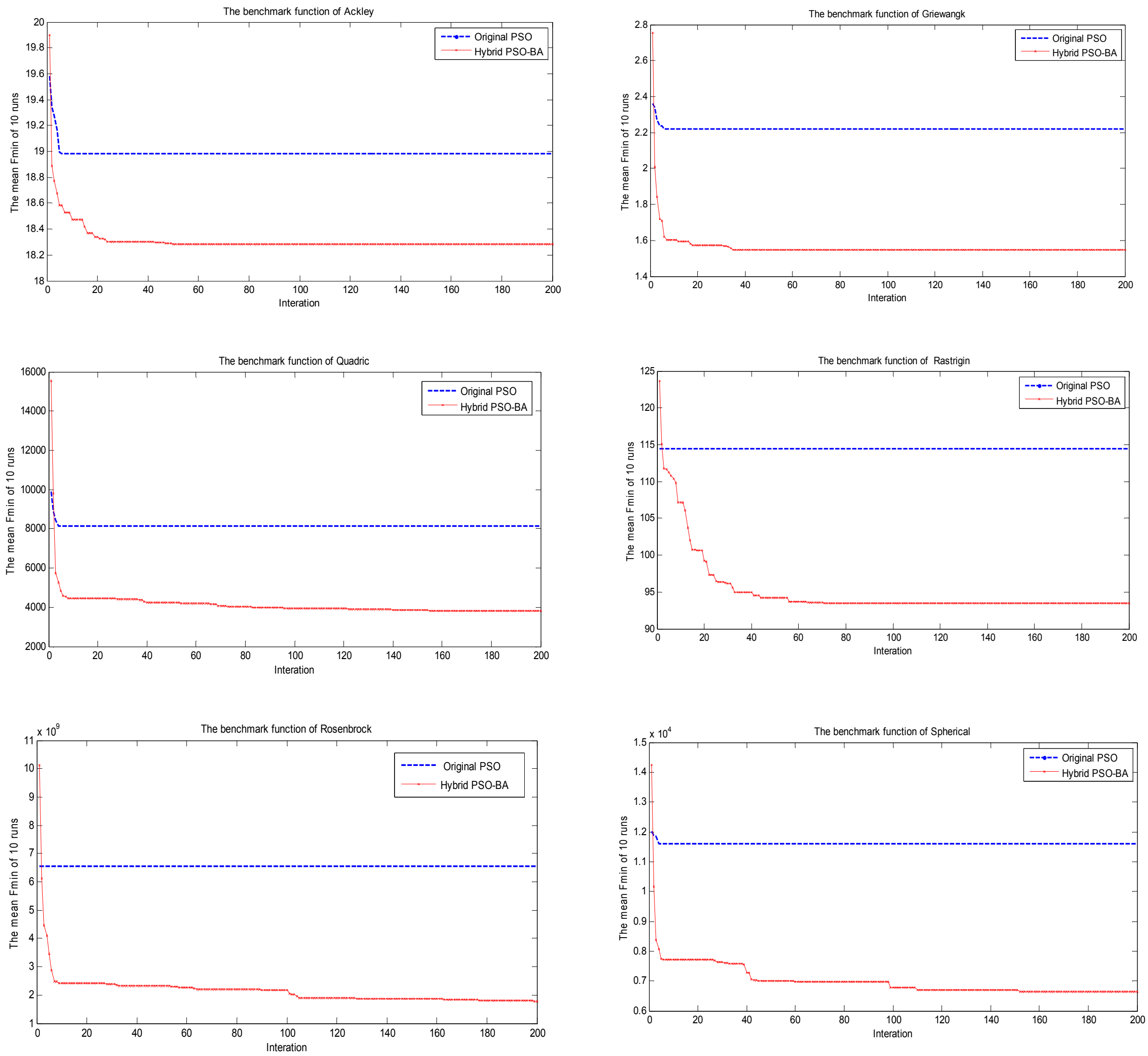

Fig. 2. The mean of function minimum curves in comparing PBA and original PSO algorithms for function of Ackley, Griewank, Quadric, Rastrigin, Rosenbrock and Spherical

Table 3 compares the quality of performance and time running for numerical problem optimization between PBA and original BA. It is clearly seen that, almost these cases of testing benchmark functions for PBA are more convergence than original BA. Average value of all benchmark functions for hybrid BA- PSO is 2.32E+07 in performance evaluation, but this figure is 2.30E+07 for original BA, reaches at 3% improvement of accuracy.

However, average times consuming of all benchmark functions for PBA is longer taken than original BA. For this result, the reason is the hybrid algorithm must perform mutation and update operations.

Table 3. The comparison between PBAand origianl BA in terms of quality performance evaluation and speed

Function	Performance evaluation		Time running evaluation (seconds)	
	BA	***Hybrid BA-PSO(PBA)***	***BA***	***Hybrid BA-PSO(PBA)***
$f_1(x)$	1.84E+01	1.65E+01	0.087	0.104
$f_2(x)$	7.37E-01	7.34E-01	0.094	0.119
$f_3(x)$	2.59E+03	2.05E+03	0.120	0.180
$f_4(x)$	4.67E+01	4.60E+01	0.087	0.098
$f_5(x)$	1.38E+08	1.38E+08	0.089	0.109
$f_6(x)$	2.65E+03	2.47E+03	0.071	0.071
Average value	**2.35E+07**	**2.30E+07**	**0.101**	**0.124**

Figure 3 shows the experimental results of six benchmark functions in running 10 seeds output with the same iteration of 200. It clearly can be seen that the most cases of curves of PBA (solid red line) are more convergent than those of BA (doted blue line).

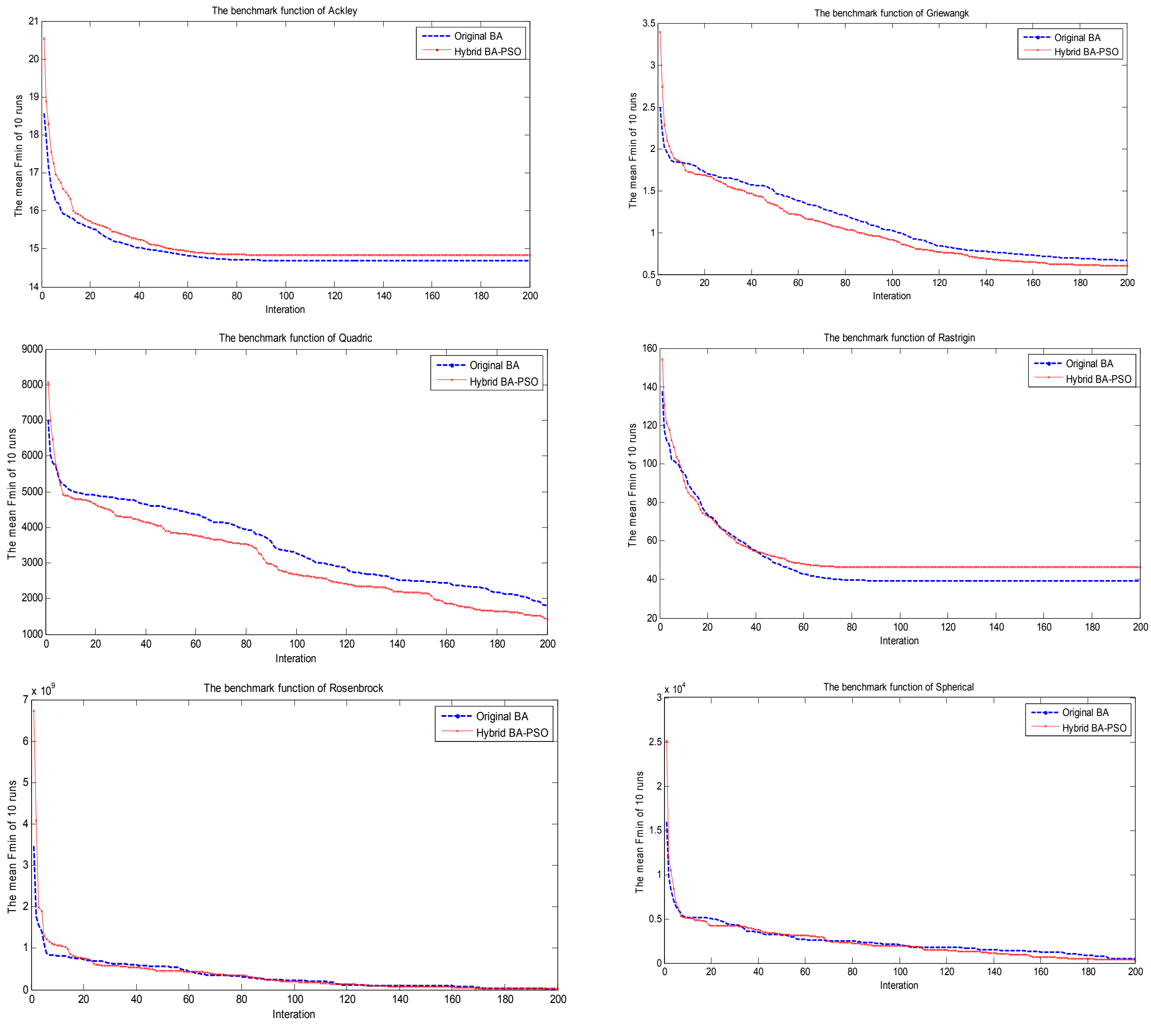

Fig. 3. The mean of function minimum curves in comparing PBA and BA algorithms for function of Ackley, Griewank, Quadric, Rastrigin, Rosenbrock and Spherical

7. Application of the Proposed PBA Method

In this section, an application of the proposed PBA method is presented to optimize BS locations in heterogeneous WSNs. The objective function for optimal BS locations in WSNs is constructed based on the residual energy application nodes, small sensor nodes and contention. The experimental results of the proposed method are compared with the PSO and BA methods.

7.1 Network Model Description

As mentioned in section 2, network model could be described as following: the heterogeneous WSN with S_M a set of SNs, V_N a set of ANs, and at least one BS are randomly distributed in desired areas. Each node can communicate with others by using *r* data transmission rate. A virtual directed graph is constructed on ANs and iteratively moves the sensors from those clusters that have the largest number of small sensors to smaller clusters. In the virtual directed graph, there is an edge $\overrightarrow{v_i v_k}$ from AN v_i to v_k if there is a sensor s_j that can be moved from the cluster of v_i to the cluster of v_k. The weight of the edge is the number of such small sensors that can be moved from the cluster of v_i to the cluster of v_k.

When all application nodes are homogeneous, i.e., their initial on-board energy are the same; the energy consumption functions are the same; and the data transmission rate is constant. In practical in WSNs, several different kinds of sensors cooperate together to fulfill some certain goals. Some sensors may generate data at a higher rate than others do, *e.g.*, the visual sensors have a bit-rate that is much higher than the bit-rate generated by a temperature sensor. Even in scenarios when all small sensors are of same type, sometimes sensors located at different locations may need to sample the data at a different time interval. Thus, it is more reasonable to assume that in a WSN different type of sensors produce different bit-rates. By assuming that every small sensor has its own data transmission rate r_j, the problem of maximizing the lifetime is formalized as follows:

$$L = \mathrm{Max}\left(\min_{v_i \in V_n} \frac{P_i}{p_i(\sum_{s_i \in S_M} r_j \cdot x_{i,j})}\right) \quad \textbf{(21)}$$

where P_i is the initial onboard energy of application node i, p_i is energy consumption function. Weight of an AN v_i for assignment x is defined as:

$$w_i(x) = \frac{p_i(\sum_{s_j \in S_M} r_j \cdot x_{i,j})}{P_i} \quad \textbf{(22)}$$

The lifetime of the heterogeneous network is defined as

$$L = \mathrm{Min}(\max(w_i(x)) \quad \textbf{(23)}$$

Subject to constraints

$$x_{i,j} = 0, \forall v_i, \forall s_j \notin N(v_i); \quad \textbf{(24)}$$

$$x_{i,j} \in \{0,1\}, \forall s_j, \forall v_i; \quad \textbf{(25)}$$

$$\sum_{v_i} x_{i,j} = 1, \forall s_j; \quad \textbf{(26)}$$

$$\sum_{s_j \in S_M} r_j \cdot x_{i,j} \le k_i, \forall v_i \quad \textbf{(27)}$$

where $k_i = p_i^{-1}(P_i \cdot T)$ let x^{min} be the solution to (23) and T^{min} be the minimum weight of the ANs. The special case when application nodes are homogeneous; its lifetime is equivalent to minimizing the maximum $\sum_{s_j \in S_M} r_j \cdot x_{i,j}$ subject to constraints (24).

If every AN v_i satisfies that $N(v_i) = (S_M - v_i)$ then the problem becomes the traditional job scheduling problem [40], which is known to be NP-Hard. Since solving (23) is NP-hard, the optimal solution is presented by an algorithm approximating by borrowing some ideas from job scheduling [41].

Fitness function is formed by equation (23) as following:

$$\mathrm{Fitness(i)} = \sum_{s_j \in S_M} r_j \cdot x_{i,j} \quad \textbf{(28)}$$

The pseudo code of the application of PBA for optimal BS location in the heterogeneous WSN is shown in Figure 4.

7.2 Experimental Results and Comparison

The environmental setting: the range of deployment of network areas set to 200x 200m; the number of agents or sensor nodes set to 2000; the number of vertices set to 20; the fixed iterations for triggered communication set to 10; the remain energy starts at energy initial for all sensor nodes set to 2.0J; the energy electronics circuit set to 50nJ/bit; the average dissipated energy for each iteration set to 0.05pJ/bit; the initial coverage of the edge $x_{(i,j)}$ randomized from 0 to 1. The parameters setting for PBA are the initial inertia weight *W=(0.9-07*rand),*

Input: Object function from equation (28).
Output: The solution to heterogeneous WSN optimization (28), the best location for BS.
1: Find a feasible solution x, *e.g.*, randomly assign every SN to a neighboring AN.
2: Construct a virtual graph *G(x)* based on *x*.
3: **repeat**
4: Choose any one of AN with the largest weight randomly, say v_i.
5: Define $w_i^+(x) = \frac{p_k(\Sigma_{s_j \epsilon S_M} r_j \cdot x_{k,j}+r)}{P_k}$
6: Find the AN v_j with the smallest $w_i^+(x)$ in $R_i(x)$. If there are more than one such ANs, choose one randomly.
7: Apply $\begin{cases} \text{procedure PBA } (v_i, v_j, F_{itness}(G_{(x)}), x); \\ \text{procedure PSO } (v_i, v_j, F_{itness}(G_{(x)}), x); \\ \text{procedure BA } (v_i, v_j, F_{itness}(G_{(x)}), x); \end{cases}$ if $w_i(x) < w_j^+(x)$
8: **until** $w_i(x) < w_j^+(x)$

Fig 4. Pseudo code of the application of PBA for optimal BS location in the heterogeneous WSN

coefficients of learning factors c_1=2.0 and c_2=2.0, the total population size $N_1 = 10$ and N_2=10, the dimension of the solution space M = 10, and initial loudness $A_i^0 = 0.25$, pulse rate $r_i^0 = 0.5$. The object functions are valuated fully iterations of 1000 repeated by 10 runs in different with random seeds. The experimental parameters are set for PSO as c_1 = 2.0, c_2 = 2.0, inertia weight *W=(0.9-07*rand)*, population size N = 20 and the maximum iteration times is 1000 in each run, for further reference in setting [36, 37]. The experimental parameters are set for BA side are the initial loudness $A_i^0 = 0.25$, pulse rate $r_i^0 = 0.5$ the total population size *N*= 20 and the dimension of the solution space *M = 10*, frequency minimum f_{min} = *the lowest of initial range function* and frequency minimum f_{max} = *the highest of initial range function.* The proposed scheme is executed for 10 runs and each run contains 1000 iterations, for further reference in setting [38].

Table 4. The comparison the proposed PBA method with the *PSO-method,* and the BA method in terms of quality performance evaluation and speed

Methods	***Population size***	***Objectives***	***Average function values***	***Consumption times(m)***	***Comparisons***
The PSO – heterogeneous WNS	*20*	*2*	*5.7023*	*11.096*	13%
The BA- heterogeneous WNS	*20*	*2*	*5.2091*	*11.106*	3%
The PBA- heterogeneous WNS	***20***	***2***	***5.0434***	***11.105***	0%

Table 4 compares the performance for optimal BS locations in heterogeneous WSNs of the proposed PBA method with the PSO-method, and BA method in terms of quality performance evaluation and speed. It is clearly seen that, the average cases of fitness functions in PBA method is as fast as convergence that original BA method cases. The method of PBA, the mean of fitness functions evaluation of minimum function 10 runs are more accuracy optimization than that in the PSO, and the BA method at 13% and 3% respectively. Moreover, the total time consuming of the proposed PBA method in 10 runs is quit fast with only 11.105 minus taken.

Figure 5 illustrates the comparison of the proposed PBA method with PSO-method and BA-method.

8. Conclusion

This paper, a novel proposed optimization scheme was presented, namely PBA (hybrid Particle Swarm Optimization with Bat Algorithm). The implementation of hybrid for optimization algorithms could have important significance for taking advantages of the power of each algorithm and achieving cooperation of optimization

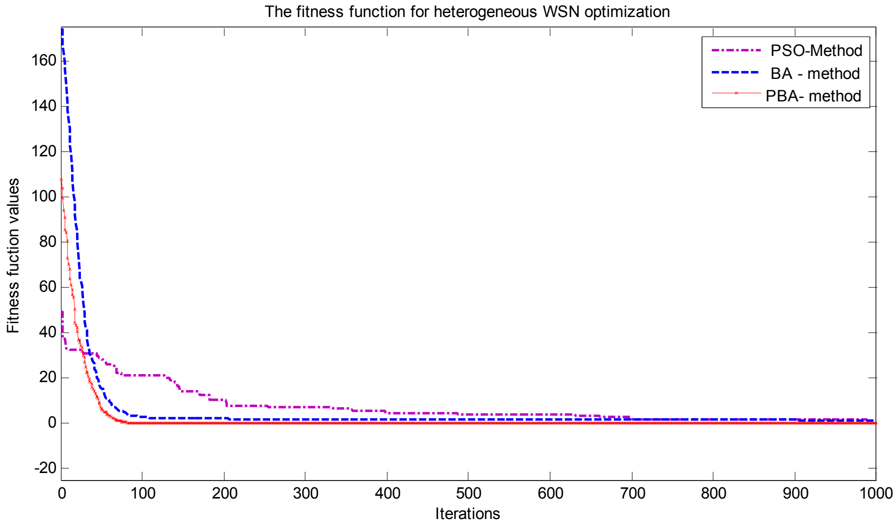

Fig. 5. The mean of minimum value of fitness function in of 10 trails in comparisons the proposed PBA method, with PSO-method and BA- method for optimal heterogeneous WSNs

algorithms. In the new proposed algorithm, the several worse individuals in PSO are replaced with the best artificial bats in BA algorithm after running some fixed iterations, and on the contrary, the poorer bats of BA are replaced with the better particles of PSO. The proposed communication strategy provides the information flow for the particles to communicate in PSO with the bats in BA. The performance of PBA algorithm is better than both original PSO and BA in terms of convergence and accuracy. The results the proposed algorithm on a set of various test problems show that PBA increases the convergence and accuracy more than original PSO and original BA is up to 47 % is at 3% on finding the best solution improvement. The proposed method is also applied to solve the problem of maximizing the system lifetime under some given constraints in wireless sensor networks (WSNs). Compared with, the particle swarm optimization (PSO) method and the Bat algorithm (BA) method, the proposed PBA method provides the most robust structure and longest network lifetime. The experimental results show the proposed PBA as an effective cooperating algorithm.

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