
Context-Aware Task Allocation in Wireless Sensor Network based on Firefly Algorithm

By

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ABSTRACT

In the scope of wireless sensor networks (WSNs), maintaining the network lifetime under energy constraint is a critical issue. Support task allocation for multiple concurrent applications in sensor networks (such as event detection and target tracking) needs available network resources and sharing applications' task (such as task workload and connectivity). This paper proposes a firefly algorithm for wireless sensor selection for task allocation to minimize energy consumption and guarantee the required Quality of Service for each application's task in wireless sensor networks. Each Firefly in Firefly Algorithm is encoded to act as a complete potential solution for task allocation. The connectivity and task workload are guaranteed by taking them as constraints for the problem. The energy level on the sensors is determined based on the light intensity on the firefly, the higher the light intensity the higher the energy. The task is allocated to the sensor with higher energy i.e. more attractive. It reduces the energy consumption among the sensors that are already exhausted and weak, it also helps in identifying the sensors with low energy. Furthermore, the performance of the Firefly algorithm has been compared with Ant Colony Optimization (ACO), Particles Swarm Optimization (PSO) and Artificial Bee Colony algorithm (ABC), the proposed method outperforms all of ABC, ACO and PSO in terms of solution quality.

Keywords: Firefly, task allocation, sensor nodes, work load, connectivity.

INTRODUCTION

In spite of the increases in network capacity (i.e. bandwidth), the quantity of sensor devices also rises proportionally, which sustains an inequality between essential bandwidth and actual bandwidth for transmitting vast quantities of sensed data. This problem continues to affect the potentiality of the environmental monitoring systems, the lack of required capacity leads to data loss at the spot of collection. Therefore, immediate resolutions have to be made about the allocation of limited network resources amongst the competing devices. This problem cannot be solved by improvements in hardware technology only, a smart software solution is also needed [1].

Task allocation has an important role to play in resource constrained Wireless Sensor Networks, sensor nodes share the workload of each task among themselves for system performance optimization and resource conservation. Consequently, after computing the processed task then it will be shared into smaller subtasks, and then the sensor nodes would execute the task independently. To be able to manage the abilities of a Wireless Sensor Networks as an efficient mechanism, a parallel computing system is vital to assign each task to an appropriate group of

nodes [2]. Most of the nodes in Wireless Sensor Network have limited energy storage and have low processing capability. Sensor nodes with the balanced energy consumption should be allocated with the task and consideration of energy conservation to extend the network lifespan [3]. In various applications, the task should be completed within a short period [4].

Many research on task allocation on distributed and parallel systems [5], [6] has difficulty to be implemented directly for Wireless Sensor Network because the energy resource is limited and so also the communication link is unstable in the wireless sensor network. To conserve the energy other research concentrates on solving task allocation problem on wireless sensor networks [7] or minimizing execution period of the task [8]. Both the Stochastic heuristic scheme [9] and Traditional heuristic scheme [10] are earlier been used in solving this problem. When Stochastic meta-heuristic algorithm uses bionic intelligence; global optimum with high efficiency can be achieve. The problem size grows exponentially and possibly trap in local optimum when a Traditional heuristic method is adopted, it also has computational complexities.

Firefly Algorithm (FA) [11] is the best among other evolutionary algorithms based on achievement rate and solution attribute [12]. Additionally, regarding suitability for the resource constrained in Wireless Sensor Network, firefly algorithm is more reliable due to its easy to implement, and it has few parameters to adjust and its simplicity [13].

In [14] true online reinforcement learning algorithm is used to achieve better energy consumption and performance trade-off. Dynamic Voltage Scaling (DVS) and Dynamic Modulation Scaling (DMS) are used for scheduling of computation tasks and communication messages in the networks respectively; to minimize energy consumption of the network, the two approaches are then compared with Mixed Integer Linear Program (MILP) to match the optimal performance.

In [16] Cross-Layered Energy-Aware Resource allocation (CLEAR) is proposed to use the characteristics of Medium Access Control (MAC) and Physical (PHY) layers of Wireless Body Area Networks (WBANs) to solve packet delivery ratio, energy consumption problems, delay and bandwidth utilization. In [17] Fuzzy-based Hyper Round Policy (FHRP) is used to reduce the clustering energy overhead and maximizing the network lifetime; and FHRP is compared with two popular clustering protocols that employ the round-based policy Extended Hybrid Energy-Efficient Distributed (EHEED) and Energy Delay Index for Trade-off (EDIT) to demonstrate the effectiveness of FHRP in network lifetime improvement and scalability. In [18] Discrete Particle Swarm Optimization (DPSO) is used through adopting a binary matrix encoding form to minimize tasks execution time, balancing network load, saving node energy cost and defining a fitness function for improving scheduling effectiveness and system reliability and Fault-tolerant Task Allocation Algorithm (FTAOA) is compared with QAFT, FTAA, EMM and TAGA. In [19] Firefly Algorithm is used to solve Clustering of nodes in Wireless Sensor Networks so as to reduce energy consumption during data transfer between the nodes. In [20] Discrete Firefly Algorithm (DFA) is used to solve hybrid flow shop scheduling problems by optimizing Makespan and mean flow time and DFA is compared with GA, PGA, ACO and SA. In [21] reverse combinatorial auction is used to maximize the network life time and enhance the quality of Service of the sensor network. In [22] semi definite programming (SDP) based centralized algorithm is used to minimize energy consumption and bandwidth utilization in wireless sensor networks. In [23] power auction and SNR auction are used for maximizing energy and flexible in trading off fairness in distributed resource allocation for

cooperative communication. In [1] online auction is proposed by allowing sensors to access resource based on cost, precision, significant changes to readings and amount of data collected. In [24] two scheme are proposed the reverse auction game theory and Energy and delay efficient distributed winner determination protocol (ED-WDP) for the purpose to minimize energy loss in the sensors. In [25] Swarm intelligence evolutionary mechanisms, Min-min and Max-min approaches are used in scheduling jobs on computational grid. In [26] Tabu search, genetic Algorithm are compared in utilizing job scheduling on computational grids to avoid trapping in local optimal solutions.

This paper proposes Firefly algorithm for resource coordination in wireless sensor networks, one of the most important contribution of this work is a task allocation scheme which emphasis on a fair energy balance among nodes constrained. Therefore, the cost formulation considers the connectivity of a certain nodes and workload of tasks as constraints for the task allocation problem. Our scheme also considered a situation in which computationally expensive task arrives while only sensor nodes with low energy are available, the nodes with lower energy will wait for another node with relatively higher amount of energy to finish its task then assign this new task to that node in order to achieve a longer network lifetime.

The paper is organized as follows: Section two present firefly algorithm, section three system model, while section four discuss on task allocation using discrete firefly algorithm section five present results and discussion and the last section is the conclusion.

FIREFLY ALGORITHM

Firefly is an insect that mostly produces short and rhythmic flashes that produced by a process of bioluminescence. The function of the flashing light is to attract partners (communication) or attract potential prey and as a protective warning toward the predator. The light intensity is varied at the distance from the eyes of the beholder. It is safe to say that the light intensity is decreased as the distance increase.

Firefly algorithm follows three idealized rules,

- a) All fireflies are unisex, so a firefly will be attracted to other fireflies regardless of gender.
- b) Attractiveness is proportional to its brightness; therefore, for one of the two flashing fireflies, the brighter one attract the less luminous one. The attractiveness is proportional to the brightness and as the distance increases both attractiveness and brightness decrease. Firefly move randomly if there is no brighter one.
- c) The glow of a firefly is determined or influenced by the landscape of the objective function. For the minimization problem, the brightness can be the reciprocal of the value of the objective function. For a maximization problem, the brightness can be proportional to the value of the objective function (Yang 2010).

Structure of firefly algorithm

In firefly algorithm, there are two major variables, which are the attractiveness and the light intensity. Firefly is attracted towards the other firefly that has brighter flash than itself. The attractiveness is dependent on the light intensity.

The light intensity thus attractiveness is inversely proportional with the particular distance r from the light source. Thus the light and attractiveness is decrease as the distance increase.

$$I(r) = I_0 e^{-\gamma r^2} \tag{1}$$

I = Light intensity,

I_0 = Light intensity at initial or original light intensity,

γ = The light absorption coefficient

r = Distance between firefly i and j

Attractiveness is proportionally to the light intensity seen by another firefly, thus attractiveness is β .

$$\beta = \beta_0 e^{-\gamma r^2} \tag{2}$$

β_0 = Attractiveness at r is 0

The distance between two fireflies can define using Cartesian distance

$$r_{ij} = |x_i - x_j| = \sqrt{\sum_{k=1}^d (x_{i,k} - x_{j,k})^2} \tag{3}$$

Firefly i is attracted toward the more attractive firefly j , the movement is defined as

$$x_i = \beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + x_i^t, \quad x_i^{t+1} = x_i^t \tag{4}$$

From equation (4), the first term is for attraction, the light absorption coefficient (γ) has limitation when it's tending to zero or its too large, if its approaching zero ($\gamma \rightarrow 0$) the brightness and attractiveness become constant, i.e., a firefly can be seen in any position, easy to complete global search. If the γ is approaching infinity or too large ($\gamma \rightarrow \infty$), the attractiveness and brightness become decrease; the firefly movements become random. While the second the term is for randomization, as α is the randomize parameter. The ϵ_t can be replaced by $\text{ran}^{-1/2}$ which is ran is random number generated from 0 to 1.

Three numerical benchmark functions namely Sphere's function, Rosenbrock's function and Ackley's function were used in the experiments for testing the performance of the proposed FA approach [27].

The range of parameters are described as follow;

Sphere Function

The sphere function is given by Eq. (5):

$$f_1(x) = \sum_{i=1}^d x_i^2 \tag{5}$$

Rosenbrock's function

Rosenbrock is a type of unimodal optimization function with mathematical representation by Eq. (6)

$$f(x) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2 \right] \tag{6}$$

Ackley function

Ackley's function is a type of multimodal function mainly applied for testing the performance of the optimization algorithms and expressed by the following mathematical

Eq. (7):

$$f(x) = 20 * \exp \left[-0.2 \sqrt{\left(\frac{1}{d} \sum_{i=1}^d x_i^2 \right)} \right] - \exp * \left[\frac{1}{d} \sum_{i=1}^d \cos(2x_i) \right] + 20 + e \quad (7)$$

System Model

The framework models of task allocation are presented in this section which includes task distribution, network distribution, and problem formulation.

Task Distribution Model

Task sharing in a wireless sensor network is computationally critical, and it also requires a lot of energy to process [2].

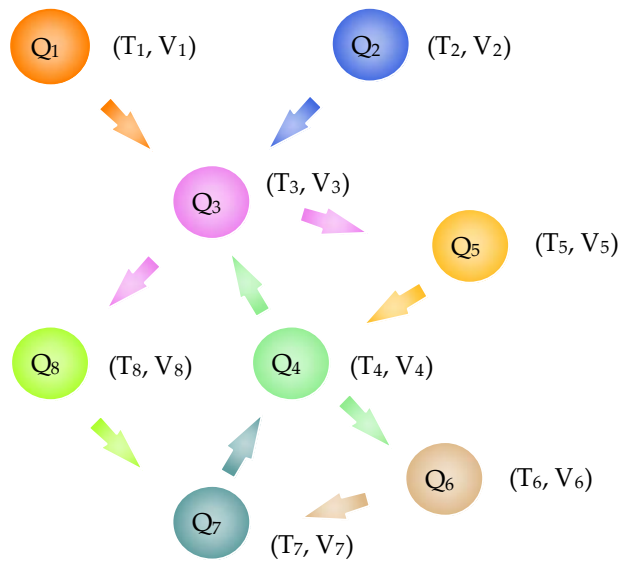


Figure 1. Task Distribution model

The Task and their dependent relationship via Directed Acyclic Graph (DAG) are shown in figure 2. Let $Q = \{Q_i : i = 1, 2, \dots, m\}$ be the task to be performed on the networks. The workload of each task is tracking and detection.

The tracking load is $T = \{T_i : i = 1, 2, \dots, m\}$ which determines the target travelling route. The detection load is $V = \{V_i : i = 1, 2, \dots, m\}$ which identify and locate the target. Supposed the workload of each task is beyond the processing ability of a single node.

$\{Q_1, Q_2, Q_3\}$, $\{Q_4, Q_5\}$ and $\{Q_6, Q_7, Q_8\}$ are the execution order of the tasks shown in Figure 2. $\{Q_1, Q_2, Q_3\}$ are the first task to be considered with urgency. Followed by task $\{Q_4, Q_5\}$ after task $\{Q_1, Q_2, Q_3\}$ are being completed. $\{Q_6, Q_7, Q_8\}$ are task to be executed at last after all the other task has been finished.

Network Distribution Model

Sensor nodes are deployed to monitoring an environment in a heterogeneous manner in Wireless Sensor Network (WSN). The features of the sensor nodes vary regarding the processing capability, energy consumption, and sensing capability. Fig. 3 shows a weighted undirected graph

$W = (S, H)$ which represents Wireless Sensor Networks. The network nodes is represented by a set of vertices $S = \{S_j : j = 1, 2, \dots, n\}$. The direct communication link among nodes (H) which is the set of edges. The communications are bidirectional and the maximum communication range are equal on all the nodes; therefore, the direction of the edges is random.

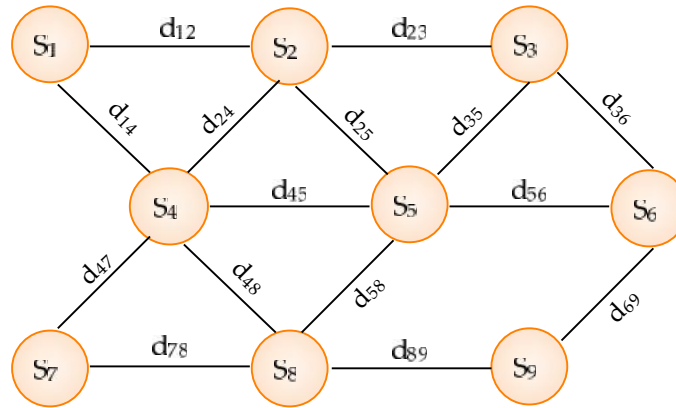


Figure 2. Network Distribution Model

Distance amongst nodes is represented by weights of edges $d = \{d_{12}, d_{23}, \dots, d_{ij}\}$. The distance between N_i and N_j is denoted as d_{ij} . The two nodes are directly connected, when the maximum communication range is greater than d_{ij} .

Adjacency matrix $C = (c_{ij})_{n \times n} \in \{0, 1\}^{n \times n}$ represents the graph W . Link among two associated nodes is determined by the value of each element in C . Let 1 signifies there is connection while 0 represents no connection. C can analyze the connectivity of the Wireless Sensor Networks.

Problem Formulation

The execution of the tasks in Wireless Sensor Network is shown in figure 4. $Q = \{Q_i : i = 1, 2, \dots, m\}$ Is set of task to be perform. $S = \{S_j : j = 1, 2, \dots, n\}$ expressed heterogeneous sensor nodes in Wireless Sensor Network. For a specific task Q_i , a set of k nodes $S_g = \{S_{g1}, S_{g2}, \dots, S_{gk}\}$ is selected, where $1 \leq k \leq n$. Then Q_i would breakdown into k subtasks $Q_i = \{Q_{i1}, Q_{i2}, \dots, Q_{ik}\}$. The subtask $Q_{ix}, \forall Q_{ix} \in Q_i, x \in \{1, 2, \dots, k\}$ is allocated to the node S_{gx} .

In the Direct Acyclic Graph each task needs distinctive workload on tracking and detection. Sufficient resource is needed by a group of nodes S_g to complete a given task Q_i . Data transmission amongst the nodes S_g should be assured by either direct connections or multi-hop connections for a particular task [2].

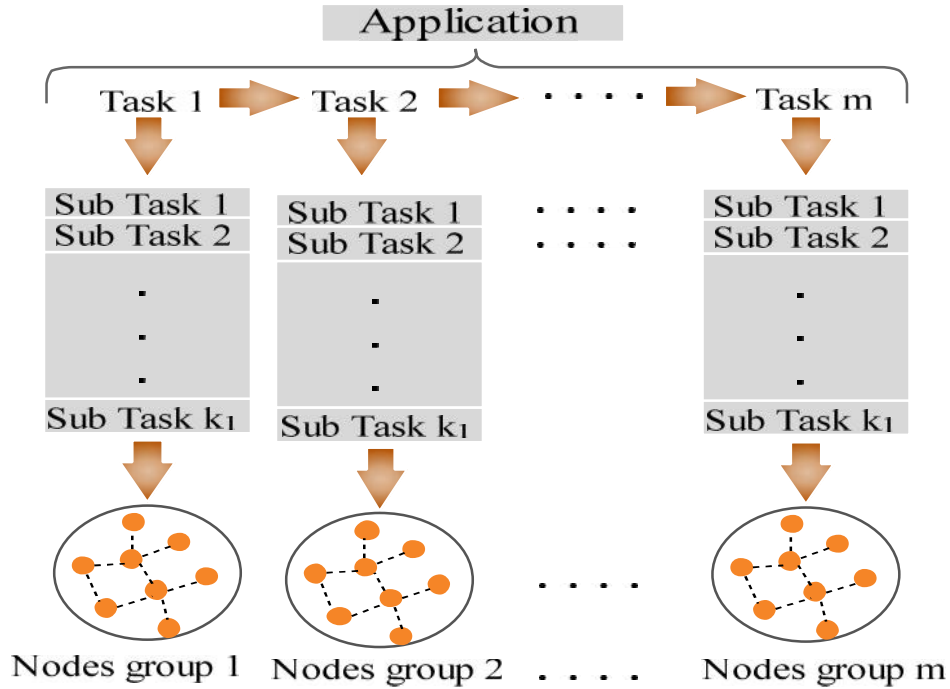


Figure 3. Task Allocation

TASK ALLOCATION USING DISCRETE FIREFLY ALGORITHM

Firefly Encoding

The position of a firefly in Discrete Firefly Algorithm (DFA) is designed as Directed Acyclic Graph to Wireless Sensor Network Graph. The tasks in the Directed Acyclic Graph have proper priorities with dependent relationships. Location of the firefly is designed $m \times n$ binary matrix as shown in figure 4, m is the total number of the tasks in the Directed Acyclic Graph while n is the total number of sensor nodes in the wireless sensor network. Order of rows in the firefly denotes the priority and the tasks dependent relationship. The task will be executed according to the priority.

A group of V firefly fly in the $m \times n$ dimensional space. The i_{th} firefly T_i is characterized by its position X_i . $X_i \in [0,1]^{m \times n}$ as shown in (8) binary matrix.

$$X_i = \begin{bmatrix} x_{i,11} & x_{i,12} & \dots & x_{i,1n} \\ x_{i,21} & x_{i,22} & \dots & x_{i,2n} \\ \vdots & \vdots & \dots & \vdots \\ x_{i,m1} & x_{i,m2} & \dots & x_{i,mm} \end{bmatrix} \tag{8}$$

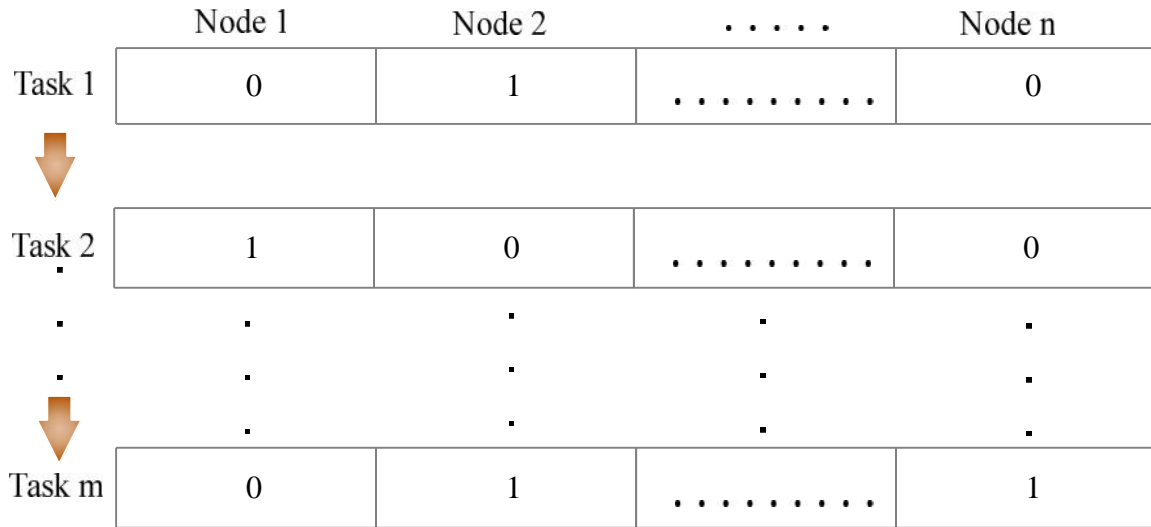


Figure 4. Firefly Encoding

X_i Indicates that specific task is allocated to a certain node. That is $x_{i,sq} \in X_i$, when $x_{i,sq} = 1$ it's imply that q_{th} task is allocated to s_{th} node. When $x_{i,sq} = 0$ it's imply that no task assign to s_{th} node.

The Constraints for Task Allocation

Sufficient resources must be assured on a particular group of nodes to complete a specific task. When initializing and updating the group of fireflies using Discrete Firefly Algorithm, the constraints on connectivity and task workload should be fulfilled.

Task Workload

From the Directed Acyclic Graph of tasks, its workload categorizes each task on tracking and detection. Each sensor has limited amount of energy and resource for tracking and detection, workload allocated to a node must be limited within a tolerable cost. Assuming each sensor can maximally perform a tracking load V_0 and detection load T_0 at a time. Assuming i_{th} task of Q_i has a total tracking load V_i and a total detection load T_i . To finish task V_i on a particular node, at least V_i/V_0 should be chosen. To finish task T_i on a particular node, at least T_i/T_0 should be chosen. From equation (9), for i_{th} task to be completed on a chosen certain number of nodes k_i , the workload Q_i should be greater than maximum cost of T_i/T_0 and V_i/V_0 .

$$\begin{cases} k_0 = \max(T_i/T_0, V_i/V_0) \\ k_i \geq k_0 \end{cases} \tag{9}$$

From equation (10), the workload assigned to each node are tracking T_s and detection V_s . The workload to the selected k_i nodes are equally distributed.

$$\begin{cases} T_s = T_i/k_i \\ V_s = V_i/k_i \end{cases} \tag{10}$$

Connectivity

To ensure data exchange the selected nodes must be connected. Undirected graph $W_M = (S_M, H_M)$ represents the selected nodes, where S_M represents selected nodes and H_M stands for direct links among nodes. W_M is a subset of the whole WSN $W = (S, H)$.

Work Flow of Discrete Firefly Algorithm (DFA)

Each firefly position is a feasible schedule for the underlying task allocation problem. Fireflies position are continuous values; it has to be converted to discrete permutations we use the Smallest Position Value (SPV). Consider $Q_i = \{Q_{i1}, Q_{i2}, \dots, Q_{ik}\}$ as the sequence of tasks implied by the firefly, The SPV rule has already been applied by the researchers to solve the task scheduling problems [20]. The proposed Discrete Firefly Algorithm (DFA) based task allocation method is going to run on the sink node which is expected to be equipped with enough resources and energy. After the execution of task allocation algorithm, the optimal task allocation scheme would be generated, for an application of Wireless Sensor Networks. Figure 4 shows the workflow of Discrete Firefly Algorithm based task allocation algorithm. Each task would then be decomposed into smaller subtasks and assigned to a selected group of sensor nodes according to the optimal scheme. The step by step implementation details is described as follows;

The pseudo-code of the DFA task allocation is illustrated in algorithm 1.

Algorithm 1: task allocation using DFA

Get the list of tasks to be scheduled;

Get the list of available resources from Sensors;

Arrange the tasks and resources in an ascending order based on task lengths and resource processing speeds (this is because SPV works with sequences);

Initialize algorithm parameters;

Generate random initial population in which each firefly represents candidate scheduling solution;

Convert the continuous values to discrete values using SPV;

Calculate the fitness values for the initial population;

While (iteration < cycles) do

For each firefly f_i do

Calculate the fitness of other fireflies using Eq(2)

Compare firefly f_i fitness with all other fireflies

If firefly f_i is the brightest firefly

Move firefly f_i randomly

Else

Move firefly f_i towards the brighter firefly using Eq(3)

End if

Convert the continuous values to discrete values using SPV;

End

RESULTS AND DISCUSSION

All the experiments were carried out using core i5 with window 7 and Matlab 2016a installed on it. The detailed description of the whole experimental setup is given in this section. Different parameters of Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Particles Swarm Optimization (PSO) and proposed Firefly Algorithm (FA) approaches are shown in Table 1.

Table 1: parameters of proposed approach and other algorithms

DFA		PSO		ACO		ABC	
Parameters		Parameters		Parameters		Parameters	
MaxIt	200	MaxIt	200	MaxIt	200	MaxIt	200
nPop	40	nPop	40	nPop	40	nPop	40
α	0.2	c_1	1.5	q	0.5	r	1
β	1	c_2	1.5				
γ	1	w	0.72				

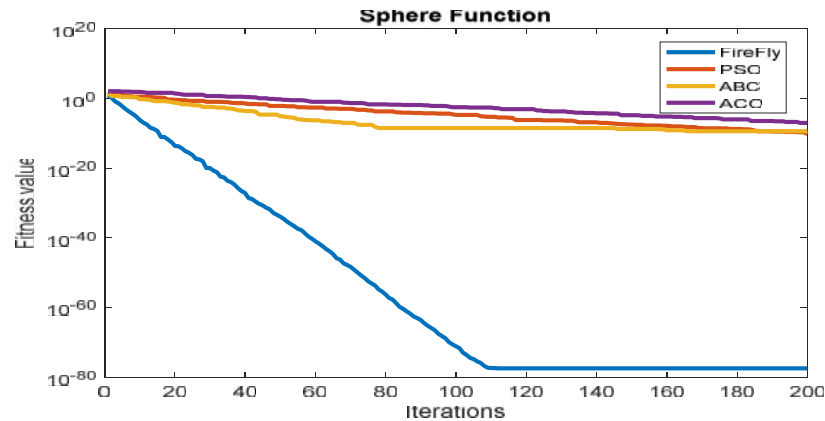


Figure 5. Convergence rates of ABC, ACO, PSO and FA for Sphere function

The proposed approach has been compared with the standard Ant Bee Colony (ABC), standard Ant Colony Optimization (ACO) and Particles Swamp Optimization (PSO) algorithms. Extensive experimentation has been carried out, for making meaningful analysis and proper comparison. All of the four algorithms namely ABC, ACO, PSO, and the proposed Firefly Algorithm (FA) results are shown in Table 2.

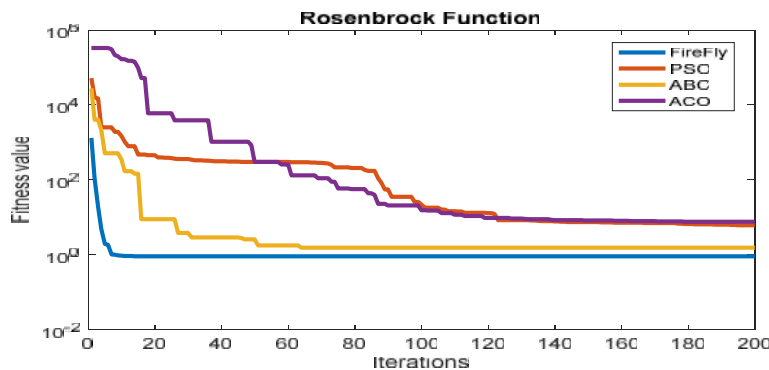


Figure 6. Convergence rates of ABC, ACO, PSO and FA for Rosenbrock function

Table 2: Comparative analysis of the proposed approach with other algorithms

Test Function	Algorithm	Best cost	Average best cost	Worst cost	Average worst cost
Sphere	ABC	3.84074E-10	2.34E-09	22.40091	6.90962
	ACO	9.19420E-08	2.36E-07	126.180	8.76771
	PSO	5.81828E-11	2.81E-10	58.2068	7.90971E-1
	Firefly	3.36383E-78	3.37E-78	7.07165	7.99863E-2
Rosenbrock	ABC	1.54107	1.56141	27804.82	835.013
	ACO	7.49245	8.20341	331870.98	32087.45
	PSO	6.02209	6.93821	51915.46	920.95980
	Firefly	9.07292E-1	9.07293E-1	1302.969	76.33825
Ackley	ABC	3.64565E-4	5.48442E-4	9.75258	1.30982
	ACO	3.15685E-4	4.73069E-4	11.1135	2.15904
	PSO	1.053413E-5	1.62E-05	7.28304	5.71853E-1
	Firefly	3.36031E-08	3.36E-08	5.60241	4.87203E-1

It is obvious from the above table that the proposed approach outperforms all the ABC, ACO and PSO algorithms for all the three benchmark functions namely Sphere, Rosenbrock and Ackley functions. The convergence rate of the four algorithms is shown in figures 5, 6 and 7 respectively. Figure 1 shows the convergence rates of ABC, ACO, PSO and the proposed approach (FA). The convergence of the sphere function is found to be much faster with FA than with ABC, ACO and PSO which is shown in figure 5. ABC, ACO and PSO are still outperformed by FA in the cases of rosenbrock function and Ackley function as shown in figure 6 and figure 7 respectively.

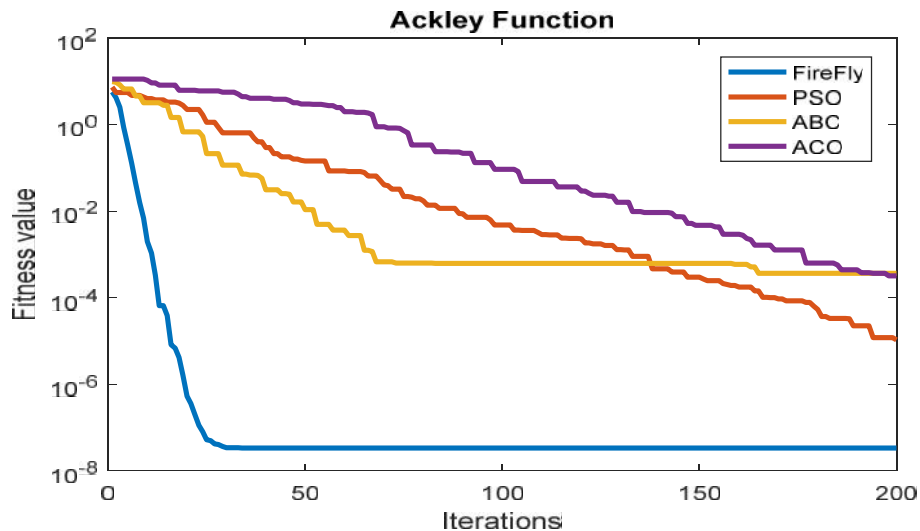


Figure 7. Convergence rates of ABC, ACO, PSO and FA for Ackley function

It can be seen with these results that FA converges much faster in all the benchmark functions with the best cost than ABC, ACO and PSO. Thus from the above results analysis, it is found that FA performs much better than ABC, ACO and PSO.

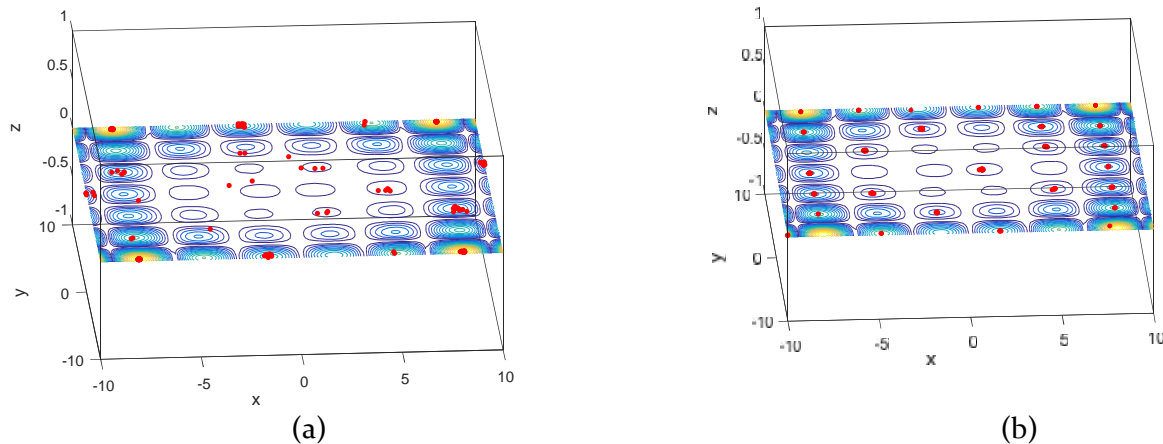


Figure 8. (a) Tracking; (b) Detection

Figure 8(a) shows the network before ensuring connectivity. The sensors that are closer can easily connect. Fig. 8(b) show that the players cooperate to achieve a social optimal allocation, some of the sensors have higher energy than the others, in these regard some of the sensors have to make sacrifice that will benefits other individual sensors. Fig. 8(b) shows that when all nodes with large energy budget are already busy, a low-power node blows its energy budget and takes on an expensive task to meet the overall time to finish the task. The sensors with higher energy are the once to perform the task in order to maximize the energy balance among the resource constrained sensor nodes. The nodes calculate their energy availability (β) for accomplishing the current task. Both α and β need to be adjusted from 0 to 1 until the best solution is reach. The best values are $\alpha = 0.2$ and $\beta = 1$.

CONCLUSION

In this article, Firefly Algorithm (FA) is employed to minimize energy consumption, guarantee the required Quality of Service and fairness in task allocation for each application's task in wireless sensor networks. In the firefly algorithm, the higher the brightness value, the better that firefly location is. That is to say; the brightness is the performance measure of fireflies. Obviously α, γ, β_0 can be adjusted to suit for solving various problems with different scales. To the author's knowledge this is the first time that the firefly algorithm has been adapted for use in task allocation in the wireless sensor networks and initial results showed it to be a superior alternative to the popular ABC, ACO, and PSO approaches.

From this article, it can be resolved that the Firefly Algorithm is robust, reliable and straightforward. It can also efficiently use for solving multilevel thresholding problem. The results are promising and encourage further research for applying them to some other complex and sensor networks analysis problems.

Conflicts of Interest

The authors declare no conflict of interest.

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