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Optimal Deployment of Wireless Sensor Networks (WSN) Based on Artificial Fish Swarm Optimization Algorithm

Lawal Samira A.[1], Garba Suleiman[2], Usman A. D.[3], Mu'azu M. B.[4], Salawudeen A. T.[5]
[1,2,3,4,5] Department of Electrical and Computer Engineering, Ahmadu Bello University; Zaria, Kaduna state, Nigeria
([1]abdulhamidsamira@yahoo.com, [2]sgarbaabu@gmail.com, [3]aliyu_d_usman@yahoo.com, [4]muazumb1@yahoo.com, [5]elteejayy@gmail.com)

Abstract- This paper presents wireless sensor network deployment using Artificial Fish Swarm Algorithm (AFSA) which works based on the heuristic behaviour of school of fish. For an effective quality of service in Wireless Sensor Network (WSN), optimal deployment of sensor nodes is an important factor. In this paper, the preying, swarming and chasing behaviours of AFSA were used to randomly and optimally deploy a total of sixty (60) sensor nodes in a network coverage area of 60 square meters. Various performance metric such as: network coverage and mobile nodes, network coverage and iteration and the effect of various attenuation factor were used to evaluate the performance of the proposed AFSA based WSN deployment model. Simulation results shows that the proposed model is valid and can successfully improve the scalability of the WSN.

Keywords- *Wireless Sensor Network; Artificial Fish Swarm Algorithm; Attenuation Factor; Coverage Area*

I. INTRODUCTION

Sensor node deployment is a crucial factor that affects the quality of service of Wireless Sensor Networks (WSNs). Inapt deployment cause low node density which leads to communication gap and high node density which creates message collisions and retransmissions, signal intrusions and cramming, huge energy consumptions, communication slit among others on the WSN. These in turn creates challenges on the scalability, stability, distributed architecture, energy consumption and autonomous operations of the WSN.

In recent years, with the development of nature inspired optimization algorithm, swarm intelligent algorithm is proved with good self-organizing and self-adapting ability, as well as strong robustness and expandability [1].These swarm optimization algorithms includes Particle Swarm Optimization (PSO) [2] Artificial Bee Colony (ABC) Algorithm [3], Bacterial Swarm Optimization (BSO) [4] Artificial Fish Swarm Algorithm AFSA [5] etc. These Algorithms have been successfully applied in solving engineering problems such as WSN deployment and tracking [6], Data clustering [7], power system stability Analysis [8], Parameter selection [9, 10] etc. Artificial Fish Swarm Algorithm (AFSA) has been widely employed in solving optimization problem due to its numerous advantages, such as: ease of implementation, strong adaptive search ability, robustness, better convergence speed, ability to acquire global extreme values and avoiding local extreme values [9].Usually, the individual Artificial Fish-AF behaviour is to hunt for local extremum which makes it difficult to move towards the global solution individually, when dealing with multi-modal complex optimization problem [9].

The rest of the paper is organized as follows: section two briefly discusses some of the related works. Section three presents the wireless sensor network model. Section four discusses the AFSA and the WSN optimization using the AFSA. Simulation results are presented in section five. Conclusion and future work makes up section six and seven respectively. Conflict declaration makes up section eight.

II. RELATED WORKS

Several researches has been conducted on the area of WSN deployment and tracking using AFS-Algorithm. To this, it has been observed that the sensitivity of AFSA to initial parameters is insignificant depending on the problem domain under consideration.

In [11] wireless sensor network deployment using an optimized AFSA was proposed. Nevertheless, network energy efficiency based on node delivery time were not considered. Ma, *et al*., [12] proposed an energy distance aware clustering protocol with dual cluster heads using niching particle swarm optimization for wireless sensor networks. In 2014, cooperative search and rescue with artificial fishes based on fish-swarm algorithm for underwater wireless sensor networks [13]. To this point however, effective coverage area utilization whilst optimally deploying mobile nodes in WSN still prompt a major concern for academic researchers. In this paper, we employed the preying, swarming and chasing behaviours of AFSA for the wireless sensor network deployment model. The proposed WSN deployment method is based on AFSA, and optimizes the capacity of finding maximal objective function value. A probability measurement model was adopted to make the algorithm more robust and significantly improves its movement from local extreme value to global extreme value at an optimal WSN coverage.

- Our Contributions: In this paper, we employed the preying, swarming and chasing behaviours of AFSA for the WSN deployment. We employed a total of 60 randomly deployed mobile nodes in a coverage area of 60 square meters. The performance of the proposed model was validated using network coverage as a performance metric. The effects of various attenuation factors were also examined.

III. WIRELESS SENSOR NETWORK MODEL

The wireless sensor network (WSN) considered in this research consists of fixed and mobile sensor nodes. A total of 60 nodes were randomly generated in a coverage area of $60m \times 60m$. The numbers of fixed and mobile sensor nodes are assumed to be N and D (where N represents the population of AFSA and D represents the dimension of deployment-usually in an optimization problem). Such that the collection of all the nodes in the network can be represented as:

$$W = \{W_1, W_2, ... W_i, ... W_{(N,D)}\} \tag{1}$$

Where W_i represent the i^{th} node in the network. Assume that $M(x, y)$ is a random point in the network coverage area and a certain node $Q\ (x_i, y_i)$ is within the monitored area. Then the distance between the nodes is [14]:

$$X(M,Q) = \|Q - M\| = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{2}$$

The probability measurement model was adopted for the detection probability of nodes Q by node M[11].

$$P_p(Q_i) = \begin{cases} 0 & R_s + R_e \le X(M,Q) \\ e^{-\alpha\lambda^{\beta}} & R_s - R_e < X(M,Q) < R_s + R_e \\ 1 & R_s - R_e \ge X(M,Q) \end{cases} \tag{3}$$

Where R_s is the perceived radius of various elements in the network, Re is the uncertain factor within the measurement range of the nodes. $0 < R_e < R_s$; α and β are measured parameters related to the physical devices; λ is the input parameters defined as [13]:

$$\lambda = X(M,P) - (R_s - R_e) \tag{4}$$

Therefore the joint detection probability of multiple sensor nodes conducting measurement simultaneously was formulated as [15]:

$$P_p(Q) = 1 - \prod_{w_i \in W} (1 - P_p(Q,M)) \tag{5}$$

A. Network Coverage Area

Network Coverage Area (NCA) is an important index to measure the strategy of the wireless sensor network deployment. In this research, the NCA is considered as the ratio of the whole area that can be covered by the nodes in the total area of node-aware and the total area of the monitoring region. Considering the complication of monitoring environment, the probability measurement model described in equation (3) was adopted. Usually to minimize consumption of energy, certain assumption needs to be made. Therefore the following assumptions were made in this study:

- Network nodes are ideal (i.e. nodes in the network have the same communication radius R_c and the same sensor radius R_s and $R_c > 2R_s$ because when communication radius between nodes is greater than two times the sensor radius of nodes, then the current networks are connected)
- Coverage is considered as a metric for the measure of quality of service of a sensor network [3].
- At the initial stage of network deployment, the nodes are randomly distributed in a square monitoring area whose length is N, the coordinate range of the monitoring area is from (0, 0) to (N, D). Where the D is the dimension of the coverage.
- The nodes obtain the coordinate position information of its own and its neighbouring nodes.
- During the algorithm, the movement of the nodes are virtual. After the end of the algorithm, nodes move to the best locations on the physical location for one time, in order to reduce consumption of energy[13, 16].
- The model and physical structure of each node are the same[17].

B. Network Area Problem Formulation

The total number of nodes (which is represented as a randomly generated artificial fish) was first defined as N. H and H' are set of total nodes and set of active nodes respectively. The inspection region of H and H' are correspondingly G and G'. The i^{th} node inspect region is G_i. The network coverage area is formulated as follows[18]:

$$\omega(H') = \left(\frac{H'}{N}\right) \tag{6}$$

The quality of the network coverage area is defined as follows:

$$C(H') = \frac{\bigcup_{i=1,2,...N} G_i}{G} \tag{7}$$

From equation (7), the objective function of the coverage quality is formulated as follows[13]:

$$\max[F(H')] = C(H') \tag{8}$$

The network region optimization was extracted into solving the optimization problem with equation (8) as the objective function.

IV. ARTIFICIAL FISH SWARM ALGORITHM

The basic idea of the Artificial Fish Swarm Algorithm (AFSA) is to imitate the fish behaviours such as preying, swarming, and chasing. The environment where an Artificial Fish (AF) lives is mainly the solution space and the states of other AFs[19]. Its next behaviour depends on its current state and its local environmental state. Usually an AF would influence the environment via its own activities and/or via the activities of its companions[20]. Mathematically, given a swarm with *N* artificial fishes, the state of one artificial fish can be formulated as:

$$X_i = (x_{i1}, x_{i2}, ..., x_{iD})\ for.i = 1,2......N \tag{9}$$

Where X_i is the status of the fish, which represent the target variable for the problem under consideration [21]. The current food concentration in the position of fish is expressed as $y = f(x_i)$ which is the objective function. The visual distance between the artificial fish is:

$$d_{i,j} = \left\| X_i - X_j \right\| \tag{10}$$

Where *i* and *j* is a randomly generated fish.

$$\left\| X_i - X_j \right\| = \sqrt{\left(X_i^2 - X_j^2 \right)} \tag{11}$$

Is the Euclidean distance between an artificial *i* and an artificial fish *j*. The detail description of the preying, swarming and chasing behaviours of AFSA are described as follows:

A. Preying

Preying is a basic biological behaviour that tends to the food; generally the fish perceives the concentration of food in water to determine the movement by vision or sense and then chooses the tendency [22].

Suppose the current state of AF is X_i, the artificial fish select a state randomly within its visual distance such that [9]:

$$X_j = X_i + rand(0,1) \times visual \tag{12}$$

Where X_j is the new state and X_i is the previous state. If $f(X_j) < f(X_i)$ in the minimum problem, it goes forward a step towards X_j in the following direction.

$$X_i^{(t+1)} = X_i^{(t)} + rand(0,1) \times step \times \frac{X_j^{(t)} - X_i^{(t)}}{\left\| X_j^{(t)} - X_i^{(t)} \right\|} \tag{13}$$

If $f(X_j) > f(X_i)$, the artificial fish selects another state randomly again. If the artificial fish cannot meet the requirement in a given time, it moves one step randomly as [10]:

$$X_i^{t+1} = X_i^t + rand(0,1) \times step \tag{14}$$

B. Swarming

The fishes assemble in groups naturally in the moving process, which is a kind of living habit that guarantees the existence of the colony to avoid dangers. Suppose the current state of the artificial fish is, X_i and nf is the number of its fellows within the visual distance, which is equal to the number of elements in the set of $B = \{X_i \mid d_{ij} \le visual\}$. If $nf \ne 0$, which means the set of element is not empty, let X_c be the centre position and Y_c stands for the fitness of the centre position. Let $X_c = \sum_j^{nf} X_j / nf$. and $Y_c = f(X_c)$. If $nf \times Y_c < \delta \times Y_i$, the area is not crowded. If $Y_c < Y_i$ the artificial fish moves one step forward towards the companions centre position.

$$X_i^{(t+1)} = X_i^{(t)} + rand(0,1) \times step \times \frac{X_c^{(t)} - X_i^{(t)}}{\left\| X_c^{(t)} - X_i^{(t)} \right\|} \tag{15}$$

Otherwise, executes the preying behaviour. The crowd factor limits the scale of swarms, and more AF only cluster at the best area, which ensures that AF move to optimum in a wide field [23].

C. Chasing

When a fish finds food, neighbouring fish will trail and reach the food. Suppose the current state of the artificial fish is X_i, and X_m stands for the best artificial fish individual within X_i's visual distance. nf Is the number of X_m's within the visual distance. $Y_m = f(X_m)$, if $Y_m < Y_i$ and $nf \times Y_m < \delta \times Y_i$ the artificial fish moves one step towards X_m [24].

$$X_i^{(t+1)} = X_i^{(t)} + rand(0,1) \times step \times \frac{X_m^{(t)} - X_i^{(t)}}{\left\| X_m^{(t)} - X_i^{(t)} \right\|} \tag{16}$$

Otherwise it executes the preying behaviour.

Step is the maximum size of the movement of artificial fish. *Visual* is the visibility region of the artificial fish. δ Is the degree of congestion factor (crowd factor) of the artificial fish.

D. Optimization Using Artificial Fish Swarm Algorithm

AFSA is an optimization algorithm which works based on the population and stochastic search behaviours of fish. AFSA uses the preying, swarming and chasing behaviours of fish to find the optimum solution to optimization problems. In this research work, the AFSA consists of mobile nodes (cluster of nodes), in which the cluster head node travels based on the nature of the objective function. All nodes are processed in accordance with the artificial fish swarm algorithm to ensure that the whole fish swarm maintains a reliable communication and maximum search scale.

The adopted procedures for the proposed method are given as follows:

- Initialize the wireless sensor nodes and select the appropriate parameters for the Artificial Fish Swarm

Algorithm (*Visual distance, Step size, crowd factor and maximum iteration number*)

- Initialize the population of AFSAW randomly which is to be deployed in the coverage area's dimension of the network and initialize the iteration to $itr = 0$
- Calculate the fitness of the current locations in the swarm Y_i (the network coverage) and update the score board with the best individuals.
- Select a new state Wj randomly using equation 11 and evaluate its fitness Yj
- Execute the three (Preying, Swarming and Chasing) behaviours of Fish as discussed in section four and update the score board with the best artificial fish found so far.
- Evaluate the fitness of the current population (Nodes) and compare with the previous fitness and update the score board with the best individuals (nodes).
- If the termination criteria is met output the current fitness value in the score board (which is the optimum solution); if not increase iteration by 1 and go back to (vi) until the best solution is found.

The flowchart implementation of the complete algorithm is as shown in Figure 1.

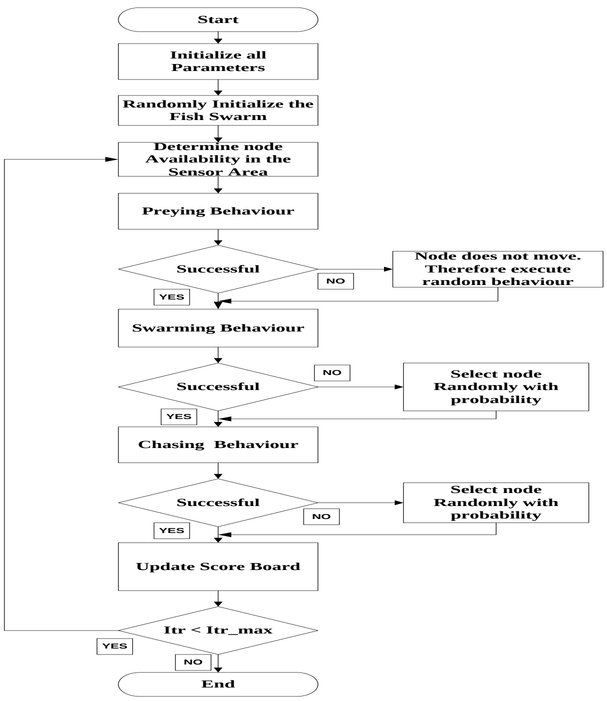

Figure 1. Flowchart of the Wireless Sensor Network Using AFSA

The visualization principle of artificial fish swarm algorithm is as given in Figure 2.

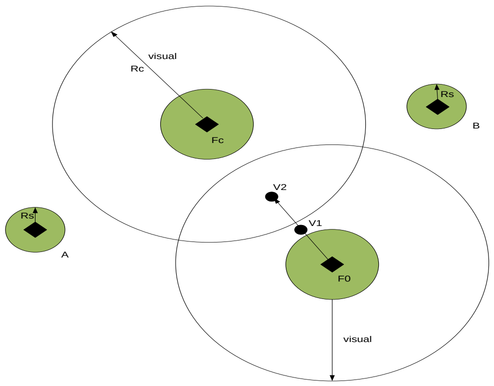

Figure 2. Geometric Visualization Principle of Artificial Fish

As shown in Figure 2, the Artificial Fish perceived the external nodes (A and B) using the information about its visualization. As indicated in the figure, F0 is the position of an artificial fish, Fc is the crowded position and V2 is the visual position at a particular point. If the position at this visual is much better than the present position, the artificial fish goes forward a step in this direction towards the V1's position otherwise it continue the search within its vision. The geometric diagram showing the network coverage for 4 nodes is shown in Figure 3.

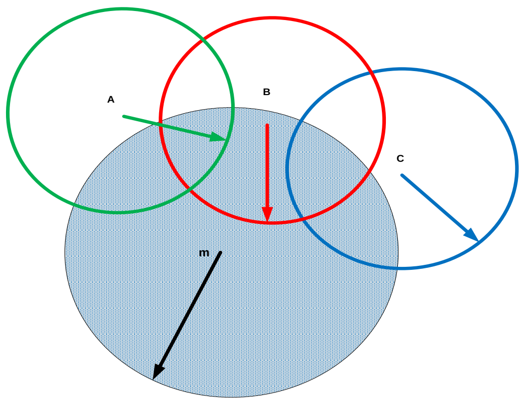

Figure 3. Geometric Diagram of Network Coverage for 4 Nodes

As shown in Figure 3, the monitored node is represented as m, while A, B and C are the neighbouring (perceived) nodes. Direct communication between the nodes exists, when the nodes intersect within the communication region of one another. Assuming the monitored node m is subdivided into N number of circles and a random circle ρ is selected from N; the network coverage for this is

$$N_c = \frac{N\left\{\min\left\{P_{\rho\in(A\cap((A\cup B)\cup C))}(S_1, S_2, S_3)\right\} \geq d_{th}\right\}}{N} \quad (17)$$

d_{th} is the threshold value of the detection probability while the entire numerator represents the number of nodes that satisfy this threshold value. N is the total number of sub-circle. S_1, S_2, S_3 are the sensor nodes for the perceived regions A, B and C.

V. SIMULATION RESULTS

The proposed model was simulated in MATLAB R2014b and the simulation results are presented in this section. Subsection A presents the parameters settings for the simulation and the model performance is presented in subsection B.

A. *Model Parameter Setting*

One of the most important metric usually considered as a measure of quality of service in wireless sensor network is the network coverage. In other to evaluate the performance of the proposed model, 60 wireless sensor nodes were randomly deployed and the problem dimension of 60 was used. Therefore, the coverage area was made 60×60 square meters. This specification was employed for all the simulation carried out in this research. All the Artificial Fish Swarm Algorithm parameters and all the network parameters are detailed in Table I.

TABLE I. AFSA AND NETWORK PARAMETERS

SN:	Parameters	Definition	Values
1	Visual	Visual Distance	20m
2	Step	Step Size of AF	10m
3	Crowd	Crowd factor of AF	0.6
4	N	Number of Nodes	60
5	Rs	Sensor Radius	4m
6	Rc	Commutation Radius	15m
7	R	Uncertain Factor	2m
8	Try_num	Number of trial	100
9	Kmin	Cessation Value	40
10	K	Current Value	Iterative
10	K_0	Initial value	200
11	R	Attenuation constant	0.95
12	Pm	Measured probability	0.8
13	K	Actuation Constant	0.4

B. *Model Performance Evaluation*

As stated earlier, Network coverage has been extensively used for measuring the performance of WSN. Therefore, the performance of the proposed model using network coverage and mobile nodes as a measure of performance is presented in Figure 4. The network coverage for every five (5) network nodes through 60 nodes were recorded and the average value of three (3) simulations performed on every five (5) interval of nodes is recorded.

Similarly, the performance of the proposed model was evaluated using network coverage and number of iterations. The average of three (3) simulations performed for every five (5) iteration through sixty (60) is recorded. The result obtained is given in Figure 5.

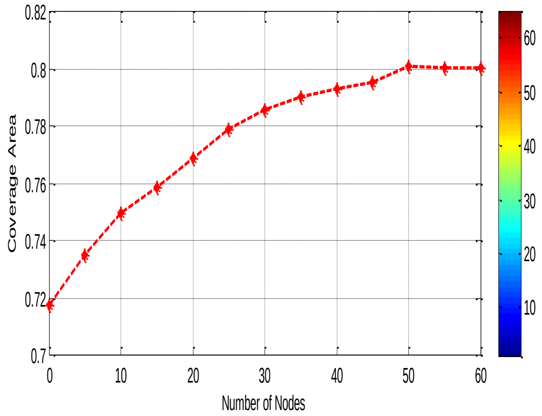

Figure 4. Relationship between Network Coverage and Network Node.

From Figure 4, it can be seen that the network coverage changes (increases) with increase in number of network nodes. The network coverage attains a maximum of 80.13% when the number of network nodes is 50. Thereafter, tends towards stability when the number of network nodes is above 50. At this point, any increase in the number of nodes has little or no significant effect on the performance of the model. This shows the convergence of the model, and hence confirmed the scalability of the network.

To establish the relationship between the network coverage and the number of iterations, the average value of network coverage after every five iteration is recorded. Figure 5 shows the graphical relationship between the network coverage and number of iteration.

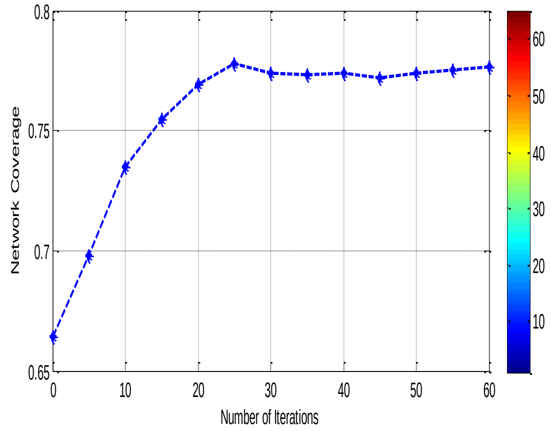

Figure 5. Relationship between Network Coverage and Number of Iterations

From Figure 6, a deduction can be made that, the network coverage changes with change in iteration. The proposed model was able to reach a maximum value of 77.87% of network coverage when the number of iteration is 25. At this point, any increase in iteration has no significant effect on the network coverage. Though, little changes can still be observed in the response after the 25 iteration, this is expected due to the random nature of wireless sensor network.

The performance of the proposed model was also evaluated under 0.75, 0.80, 0.85 and 0.90 attenuation factors. Similarly, the average of three (3) simulation performed for every attenuation factor were recorded and Figure 6, shows the behaviour of the network under the various attenuation factors.

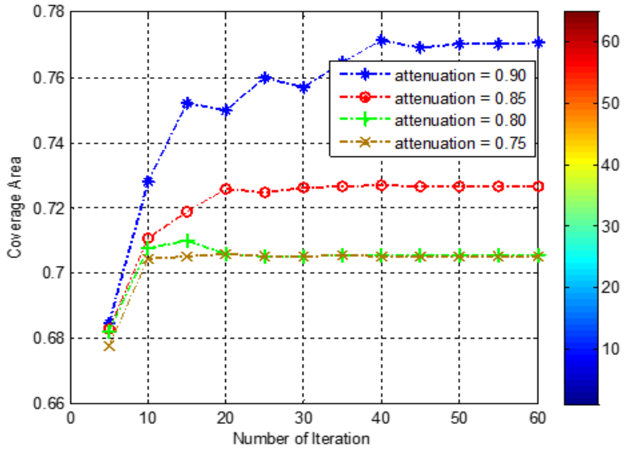

Figure 6: Effect of Attenuation on Network Coverage and Number of Iteration.

It can be observed from Figure 6, that, when the attenuation factor is 0.75 the network coverage attains its maximum at 70.58% thereafter become stable all through the simulation process. When the attenuation factor is 0.80 the network coverage attains its maximum at 70.99% for 15 iteration, thereafter becomes stable at 20 iteration and all through the simulation process. For attenuation factor of 0.85, the maximum coverage attained by the network is 72.69% which occurs at 40 iterations. Similarly, the maximum network coverage of the network when the attenuation factor is 0.90 is 77.15% which occurs when the number of iteration is 40. The minor difference in the network coverage (maximum and minimum) indicates the model converge and therefore has improve the scalability of the Wireless Sensor Network (WSN) model.

VI. CONCLUSION

This paper has presented Wireless Sensor Network deployment using artificial fish swarm optimization algorithm. The performance of the proposed model was evaluated using network coverage as a performance metric and effect of attenuation factors on the model were also investigated. Simulation result shows that, the proposed model is valid and has an improved performance when compared with other swarm algorithm based WSN deployment.

VII. FUTURE WORK

Maximum network coverage utilization and tracking of targets in WSN has proven to be a serious research problem for researchers. Though this research work has successfully proposed WSN deployment, a lot of research work still needs to be done on the area of WSN. In our future research work, we will be proposing an improved WSN deployment based on improved Artificial Fish Swarm Optimization Algorithm. Locating and tracking of targets based on the improved AFSA at maximum energy utilization will also be investigated.

VIII. CONFLICT OF INTEREST

All the parties involved in this research paper declares “NO CONFLICT OF INTEREST”.

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Lawal Samira Abdulhamid was born in Kano State Nigeria on 2nd Nov.1986. She obtained her B.Eng (electrical engineering) from Ahmadu Bello University, Zaria, Nigeria in 2009. She is currently undergoing research for her MSc. (communication engineering) from the same university. Her areas of interests include; Wireless Sensor Networks, Wireless and Mobile Communications, Network Security, Network Management and Artificial Intelligence.

Suleiman Garba has a PhD in Electrical Engineering with specializations in Wireless Communications and Networks. He obtained his B.Eng (electrical engineering) in 2000, MSc. (electrical engineering) in 2004 and PhD (electrical engineering) in 2011 from Ahmadu Bello University Zaria, Nigeria. He has authored several refereed technical journal articles and conference proceedings. His research interests include; Fuzzy Time Series Forecasting, NeuroFuzzy, Wireless and Mobile Communication, Network Security and Artificial Intelligence.

A D Usman was born in Rigachikun, Kaduna State of Nigeria on 1st January 1970. He obtained his Master of Engineering Degree from Bayero University Kano, Nigeria in 2006 and PhD (electrical engineering) with specialization in Biomed and Microwave Engineering from University Putra Malaysia (UPM), Malaysia in 2011. He has authored more than 35 National and International publications from reputable journals and conferences.

Dr. Usman is a member of Institute of Electrical and Electronic Engineers (IEEE), Nigerian Society of Engineers (MNSE), Nigerian Institute of Physics (MNIP), Member National Solar Energy of Nigeria (MNSEN) and a Registered Engineer with Council for Regulation of Engineering Practice in Nigeria (COREN).

Muhammad Bashir Mu'azu is a Professor of Control Systems. He obtained his B.Eng (electrical engineering) in 1991, MSc. (electrical engineering) in 2001 and PhD (electrical engineering) with specialization in Computational Intelligence in 2006 from Ahmadu Bello University Zaria, Nigeria. He has authored several refereed technical journal articles and conference proceedings. His research interests include; Control System Dynamics, Modeling and Optimization, Fuzzy Time Series Forecasting and Artificial Intelligence Optimization.

Ahmed Tijani Salawudeen was born in Kogi state Nigeria on 5th march, 1988. He obtained his B.Eng (electrical engineering) from Ahmadu Bello University Zaria, Nigeria in 2011 and MSc. (control engineering) in 2015 from the same university. His area of interest includes; Artificial Intelligence, WSN deployment, Bio-inspired Optimization and Control System Dynamics.