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A Study on the Applications of Particle Swarm Optimization in Wireless Communication System Using MATLAB ®

[1]Olaniran Lukman Olatinwo, [2*]Frederick OjiemhendeEhiagwina,[3]John OlusegunAzanubi, [4]Kuponiyi Bamidele
[1-4]*Department of Electrical/Electronic Engineering, Federal Polytechnic Offa, Offa, Kwara State, Nigeria*

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ABSTRACT: When designing a communication system, many problems are formulated as an optimization problem. To solve these, optimization techniques such as genetic algorithm and particle swarm optimization are required. Particle swarm optimization is inspired by flocking birds and a school of fish. The implementation is simple, although they are more complex in terms of computation time than the classical gradient technique. The need to overcome the inherent shortcoming of the particle swarm algorithm such as low searching algorithm and premature convergence has necessitated the development of variants of standard PSO. The PSO or its modifications have been applied to several areas such as in solving NP-hard problems, mechanical engineering, and digital signal processing, and so on. It has attracted the interest of wireless communications system designers, who have used it to solve optimization problems associated with communication systems. In this proposal, a survey of literature reporting applications of PSO to multi-input multi-output systems, orthogonal frequency division multiplexing, channel assignment problem, spectrum and interference management, cognitive radio network, etc. will be done. The authors also reviewed applications to wireless communication devices such as the design of filters, antennas, amplifiers, and waveguides. Besides, this research will also demonstrate a case study application of PSO to WSN clustering using Matlab®. The investigative study will help readers and practitioners alike with scholarly resource needed for understanding the state-of-the-art in this regard, and to see areas for further research. It will also help researchers to see potential collaborators in future works involving PSO applications to wireless systems.

Keywords: Amplifiers, antenna, particle swarm optimization, Wireless sensor network, clustering, wireless Communication system

I. INTRODUCTION

When designing a communication system, many problems are formulated as an optimization problem. To solve these, optimization techniques such as genetic algorithm and particle swarm optimization are required. Particle swarm optimization is motivated by flocking birds and a school of fish. The implementation, in terms of the amount and level of mathematical operations required, is simple and easily applied, although they are more complex in terms of computation than classical gradient technique. Also, it is more efficient in finding an optimal or near-optimal solution than a genetic algorithm (GA). When compared with other evolutionary-based algorithms, the PSO algorithm is faster, cheaper, efficient, and with fewer adjustable parameters. It is assumed that the particle can exchange information, thus able to recall the best position in the search space it has previously visited.

1.1. Particle Swarm Optimization Algorithm

In standard optimization, the objective or fitness function is $f\left(x_i\left(t\right)\right)$. Each particle $x_i\left(t\right)$ in the swarm has a position vector $i \in N$ with velocity vector $v_i\left(t\right)$ time t. The number of particles in the swarm is N. The position at which each particle takes the best fitness function is called the particle personal best position $x_i^p\left(t\right)$. But the overall best for all particles in the swarm is known as the global best position $x^g\left(t\right)$.

Both the particle position and velocity are updated according to

$$x_i\left(t+1\right) = x_i\left(t\right) + v_i\left(t+1\right) \quad (1)$$

$$v_i\left(t+1\right) = \omega v_i\left(t\right) + c_1 r_1\left(x_i^p\left(t\right) - x_i\left(t\right)\right) + c_2 r_2\left(x^g\left(t\right) - x_i\left(t\right)\right) \quad (2)$$

$$x_i\left(0\right) \sim u\left(x_{\min}, x_{\max}\right)$$

Where:

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ω = inertia weight
c_1 and c_2 = acceleration coefficients
r_1 and r_2 = random numbers between zero and one
$u(x_{\min}, x_{\max})$ represents the uniform distribution of the minimum and maximum value of the position

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \frac{1}{t_{\max}} \qquad (3)$$

One terminating criteria for the algorithm for the personal best and global best is indicated in

$$x^p(t) = \begin{cases} x_i^p(t) & \text{if } f(x_i(t+1)) > x_i^p \\ x_i(t) & \text{if } f(x_i(t+1)) \le x_i^p \end{cases} \qquad (4)$$

$$x^g(t) = \min\{x_i^p(t)\} \quad i \in [1, \cdots n], n > 1 \qquad (5)$$

1.2. Variants ofParticle Swarm Optimization Techniques

The standard PSO have the possibility of convergence in a local minimum increasing with the swarm dimension. To overcome this inherent shortcoming of the particle swarm algorithm, and other issues such as low searching algorithm and slow convergence have necessitated the development of variants to the standard PSO algorithm. According to Zhang et al (Zhang, Wang, & Ji, 2015) modifications, hybrids or extensions of particle swarm optimization technique include bare-bone PSO (BBPSO), quantum-behaved PSO (QPSO), chaotic PSO (CPSO), adaptive chaotic PSO (ACPSO), adaptive chaotic embedded PSO (ACEPSO), fuzzy PSO (FPSO), PSO with time-varying acceleration coefficient (PSOTVAC), iteration PSO with time-varying acceleration coefficient (IPSO-TVAC), and opposition-based PSO (OPSO). Others are standard PSO (SPSO), PSO with age-group topology (PSOAG), synchronous PSO (S-PSO), asynchronous PSO (A-PSO), random asynchronous PSO (RA-PSO), fusion-global-local topology PSO (FGLT-PSO).

Some other forms of PSO include PSO with increasing topology connectivity (PSO-ITC), adaptive PSO (APSO), knowledge-based heuristic PSO with adjustment strategies (KHPSOA), augmented PSO (AugPSO), genetic algorithm combined with PSO (PSO-GA), PSO algorithm based on improved artificial immune network (IAINPSO), PSO-based support vector machine (PSO-SVM), tabu list PSO (TL-PSO), essential particle PSO queen (ESPSOq), multiobjective fuzzy ant colony optimization (MOPSO-FACO), and hybrid-MOPSO-FACO (H- MOPSO-FACO). The aforementioned variants of the PSO algorithm are by no means exhaustive. And more modifications, extensions and hybrid of the particle swarm optimization techniques are expected as researchers continue to seek ways to efficiently apply it in resolving existing design problems. Figure 1 is a block showing examples of modifications to the PSOalgorithm.

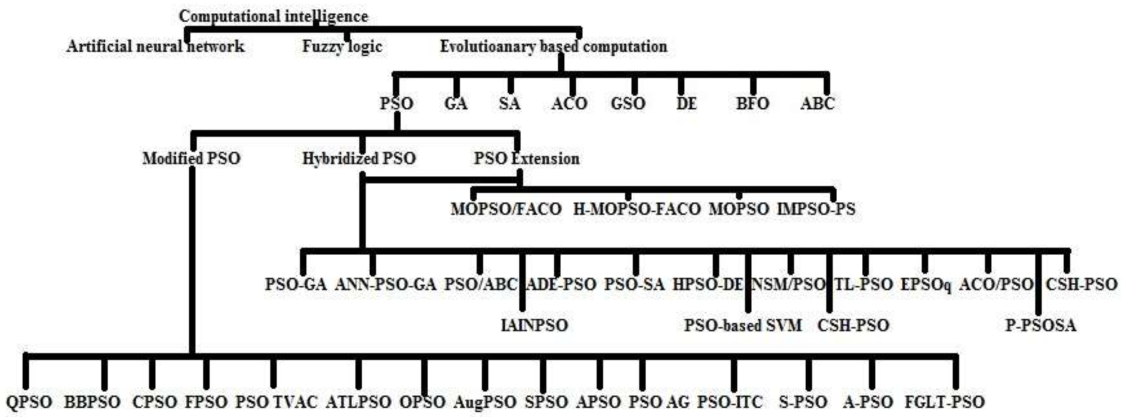

Figure 1: Examples of PSO modifications, hybrids and extensions

2. Review of Related Works on Particle Swarm Optimization

Owing to its implementation simplicity, a particle swarm optimizer has been applied in resolving several optimization fields of research. Examples are outlined as follows. Authors like Yan et al (2012) applied the PSO technique in finding solutions to the travelling salesman problem, a non-deterministic polynomial – applicable to printed circuit drilling. Shin and Kita (2012) applied PSO in solving two-dimensional packing problem.

Yusof et al (2015) proposed a blind navigation and path planning algorithm based on PSO capable of computing the shortest path. To simplify the algorithm, the authors assumed that there is no obstacle in the pedestrian path.

In (Marini & Walczak, 2015), Marini and Walczak presented a tutorial on PSO and the possibility of applying it to chemometric. There are several reported applications of PSO algorithm to image processing such as Synthetic aperture radar (SAR) image segmentation (Ma, Zhang, Tian, & Lu, 2008) where PSO and Grey entropy, target identification in foliage environment based on chaotic PSO-SVM (You & Jiang, 2014), and segmentation of satellite images based on chaotic Darwinian PSO algorithm (Suresh & Lal, 2017). Moreover, particle swarm optimizer has been applied to intricate medical signal processing, as in designing the dimensions of a cuboid for attenuating the noise in heart sound signal (Zeng & Dong, 2014), medical image segmentation scheme (Ait-Aoudia, Guerrout, & Mahiou, 2014), and detection of emotion from electroencephalogram (Mehmood & Lee, 2016).

Observing that the application of the PSO algorithm is gaining popularity among scholar, Poli (2008), categorized reported PSO applications in the literature into 26 cases such as biomedical, communication networks, control, electronics, and so on.

There is a growing interest in the use of PSO technique to solved emerging problems in wireless communications such as channel assignment, resource allocation, optimal design of the amplifier, antenna, filter, waveguide, and so on as will be justified in this proposal, especially from the mid-2000s, after the initial phase of PSO appreciation. Therefore, a survey of articles in this regard is needed that will equip upcoming researchers and expert alike with the state-of-the-art applications of particle swarm optimization algorithm to wireless communication systems. This investigation will further enhance appreciation for the PSO algorithm and consequently may lead to writing more application - case papers. To the best of our knowledge, there is no article so far that has comprehensively surveyed literature published on PSO based applications to wireless communications systems and devices.

The particle swarm optimization technique is gaining increasing interest among researchers. Few studies have investigated in the way of a survey the numerous applications of Particle swarm optimization to the communication system. This optimization technique is not fully domesticated in the Nigerian research realm. Thegoal of this proposed research isto investigate the applications of particle swarm optimization in wireless communication system and demonstrate an application case using Matlab. The objectives are to do a qualitative literature search, critically survey available literature and demonstrate a case study application of PSO using Matlab® software.

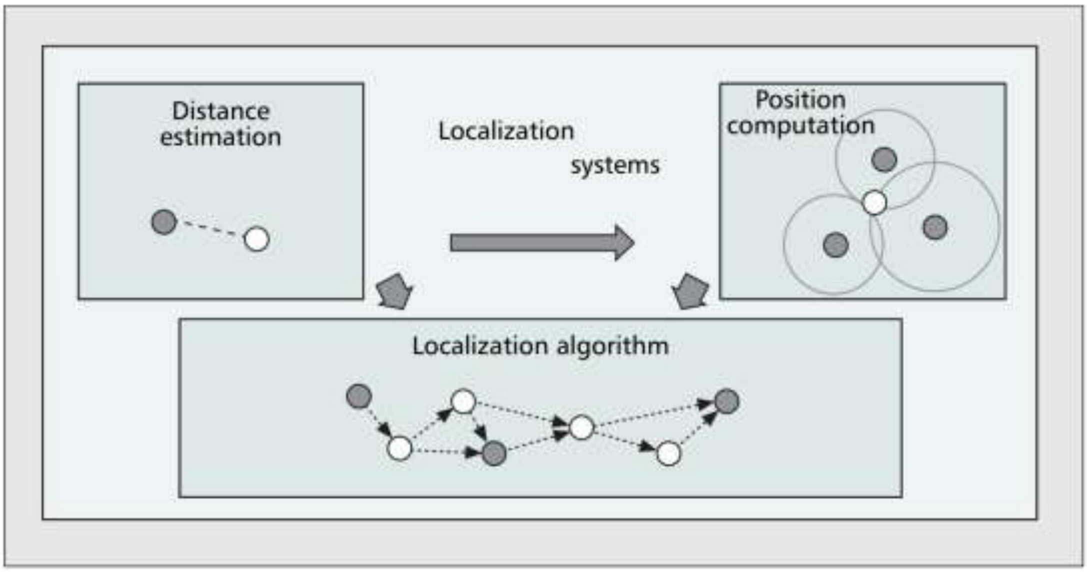

Figure 2:Components of localization in a WSN (Boukerche et al., 2007)

A key aspect of WSN is node localization refers to creating location awareness in deployed nodes (Boukerche et al, 2007). Location information is used in geometric aware routing (Aspnes, 2006). An obvious method of localization is to equip each node with a global positioning system (GPS), which is not attractive because of cost, size, and power constraints. Many WSN localization algorithms estimate locations using a priori knowledge of the coordinates of special

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nodes called beacons, landmarks, or anchors. WSN localization is a two-phase process. In the ranging phase, the nodes estimate their distances from beacons usingsignal-propagationtimeorstrengthofthereceivedsignal.The signalpropagation time is estimated through measurement of time of arrival, round-trip time of flight or time difference of arrival of the signal (Mao et al, 2007). Precise measurement of these parameters is not possible due to noise; therefore, the results of such localization is inaccurate as shown in Figure 2. In the estimation phase, the position of the target nodes is estimated using the ranging information either by solving simultaneous equations or by an optimization algorithm that minimizes localization error.

In this paper, we limited our efforts to reviewing literature published on PSO based applications to various aspects of wireless communication system between 2006 and 2017. Also, a case study application of PSO to WSN clustering using Matlab® software was demonstrated.

A Case Application of PSO to WSN Clustering Protocol

We assume that a set of static sensor nodes is randomly deployed throughout a two-dimensional square field. Sensor nodes are location-unaware and non-rechargeable. We used the realistic energy consumption model which is based on the characteristics of the Chipcon CC2420 radio transceiver data sheet (2014). The total energy consumed by node i, E_i, is calculated as in Eqn.(6):

$$E_i = \sum_{statej} P_{statej} \times t_{statej} + \sum E_{transitions}$$

(6)

The index statej refers to the energy states of the sensor: sleep, reception, or transmission. P_{statej} is the power consumed in each statej, and t_{statej} is the time spent in the corresponding state. Moreover, the energy spent in transitions between states, $E_{transitions}$, is also added to the node's total energy consumption.

The set-up phase starts with neighbour discovery where each sensor node in the network broadcast a HELLO packetthat includes its ID. A sensor node that receives this HELLO packet will update its neighbour table with the ID included in the packet along with the Received Signal Strength Indicator (RSSI) value in the received packet. After the neighbour discovery ends by all the sensor nodes, the protocol uses the flooding method to transfer the control data to the BS. Each node broadcast the following data about itself: ID, residual energy and its neighbour table data. A node that receives this packet will rebroadcast it till it reaches the BS. Based on the information the BS received, the BS runs the PSO algorithm to find the best K CHs. Each particle's position vector which represents the CH nodes IDs is initialized with random integer values in the range [1, networksize−1] where node ID 0 represents the BS. Only nodes with an energy level above the average are eligible to be CH candidate for this round to ensure that only nodes with sufficient energy are selected as CHs. The particle size is equal to the upper bound on the number of CH candidates. It should be noted that the velocity update by (2a) gives non-integer velocity values, which are converted to the nearest integer in the implementation. In the case that a particle generates duplicate ID's while initialization or after position update, the unique ID's generated are used as CH candidates as illustrated in Figure 3.
The best CHs are selected such that they optimize the combined effect of the following properties: energy efficiency, link quality, and network coverage.

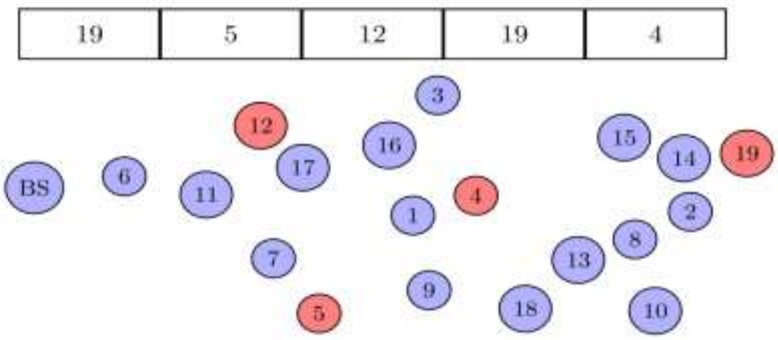

Figure 3: Example of two different particles and their respective CH candidates, upper bound = 5, red nodes are CHs

To save more energy, the protocol needs to minimize the number of active CHs during each round. This can be achieved by minimizing Eqn. (7) :

$$EE1_p = \frac{K}{D}$$

(7)

To balance the energy consumption among the network nodes, the role of the CH should be rotated between the nodes. The BS uses the following sub-objective to balance the energy consumption among the network nodes:

$$EE2_p = \sum_{k=1}^{K} \frac{initialE(CH_{p,k})}{E(CH_{p,k})}$$

(8)

K is the total number of CH candidates. D is the upper bound on the number of CHs. initialE(CHp,k) is the initial energy of CH number k in particle p. E(CHp,k) is the remaining energy for that CH. RSSI can provide a quick and accurate estimate of whether a link is of very good quality (Srinivasan, Dutta, Tavakoli& Levis, 2010). Let LQ(ni,CHp,k) be an indicator of the link quality between cluster member ni and CH number k in particle p. It can be calculated using Eqn. (9):

$$LQ_{(n_i, CH_{p,k})} = \frac{RSSI(n_i, CH_{p,k})}{minRSSI}$$

(9)

RSSI(n_i, CHp,k) is the RSSI for the link from ni to CHp,k and minRSSI is the worst RSSI value among all communicating pairs. The higher the value of LQ, the worse is the link quality. To maximize the cluster quality in terms of link quality, the following sub-objective needs to be minimized:

$$CQ_p = \max_{k=1,2,\dots,K} \frac{\sum_{\forall n_i \in C_{p_j,k}} LQ_{(n_i, CH_{p,k})}}{|C_{p,k}|}$$

(10)

|Cp,k| is the number of members in cluster k of particle p. The previous equation tries to minimize the worst link quality among all the clusters.

‘PseudoCode for the PSO system

For each particle
Initialize particle
END
Do
For each particle
    Calculate fitness value
If the fitness value is better thanthe best fitness value (pBest) in history set current value as the new pBest
End
Choose the particle with the best fitness value of all the particles asthegBest
For each particle
Calculate particle velocity according to equation (1) Update particle position according to equation (2)
End

While maximum iterations or minimum error criteria are not reached, Particlesspeeds on each dimension are clamped to a maximum Vmax speed. If the sum of accelerations would cause that dimension to exceed Vmax, which is a user-specified parameter. Then this dimension's velocity is limited to Vmax.

II. RESULT AND DISCUSS

The simulations were performed on MATLAB® using 8 different network sizes up to 400 wireless sensor nodes, and each network was tested using 5 different random seeds. The sensor nodes were deployed randomly in an area of 100m×100m sensor field. The protocol runs for 50 rounds. The upper bound on the number of CHs was set to 5% of the total nodes. The PSO algorithm used 50 particles and run for 500 iterations.

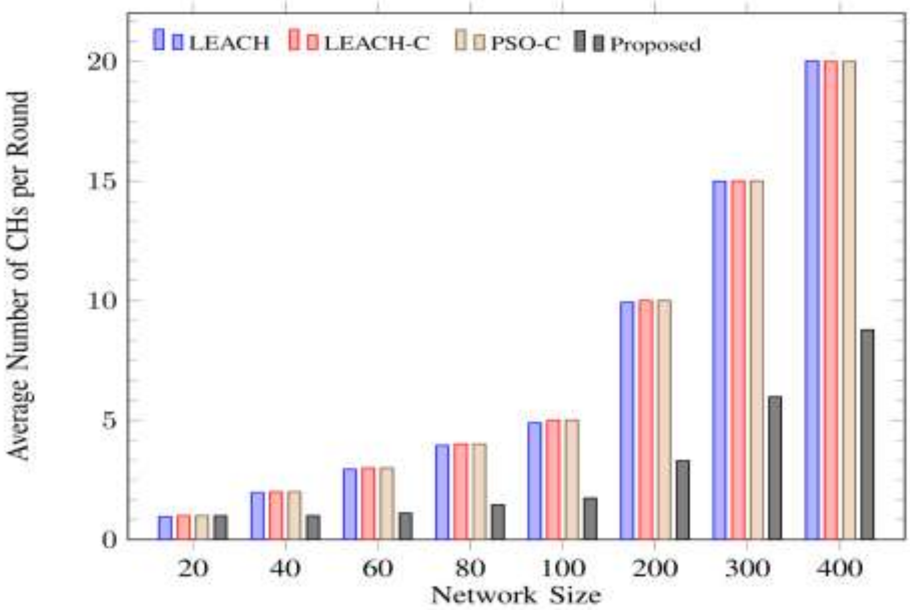

Figure 4: Average Number of CHs per Round

Figure4demonstrate that the proposed protocol outperforms the other protocols in terms of the number of CHs used.

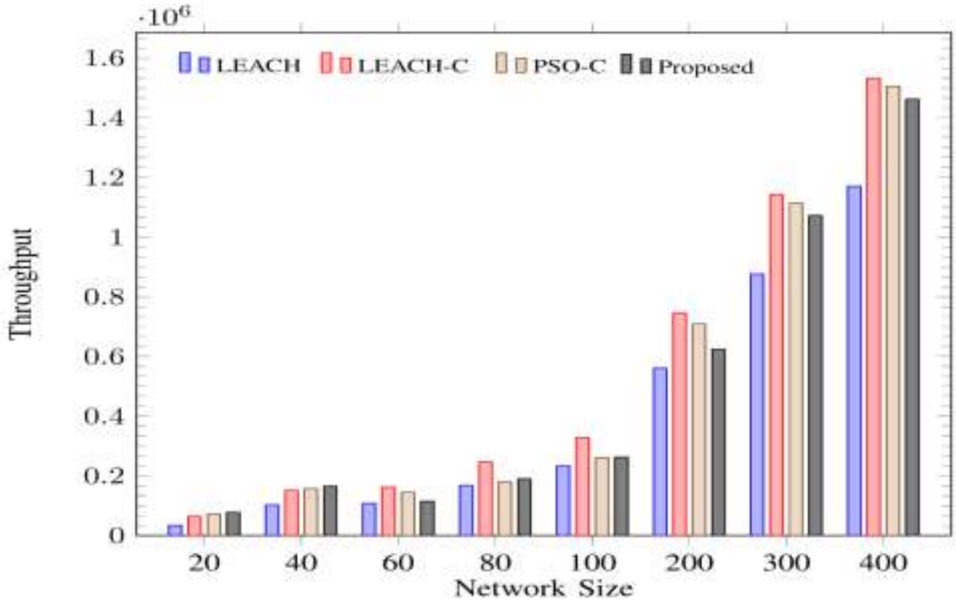

Figure 5:Throughput for the packets received by all the CHs

Figure 5: depicts the throughput calculated for the packets received by all the CHs. Although the proposed protocol outperforms the other protocol in terms of average energy consumption and network lifetime, it still has acceptable throughput compared to the other protocols.

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IV. CONCLUSION

The protocol introduced improved WSN energy efficiency via limiting the number of CHs. Matlab simulations results indicated that the proposed protocol can enhance the energy efficiency of WSN without sacrificing acceptable data packets throughput. There will be a need to work tomaximize the data transmission reliability at the WSN base station. Another area for research focus is the minimization of the total energy demand of the wireless sensor network and extend the life of the network.

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