Transmission Power Reduction Based on an Enhanced Particle Swarm Optimization Algorithm in Wireless Sensor Network for Internet of Things

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Abstract—**A wireless sensor network (WSN) consists of several sensor nodes; all these nodes can sense physical events, including light, heat, and pressure. These networks are essential in smart homes, smart agriculture, and smart water management, swelling with the concept of the Internet of Things. However, WSN needs to address the challenges of energy issues; thus, energy-conserving techniques have been pursued for communication. Optimization of energy is normally solved using the Particle Swarm Optimization (PSO) algorithm since it offers high accuracy but is prone to local optima, thus resulting in early convergence. To tackle this challenge, this paper proposes the development of an enhanced particle swarm optimization for the node power estimation (EPSO-NPE) model. EPSO-NPE calculates distinct transmission powers for each node, preventing the formation of isolated areas within a sensor cluster. Unlike the original PSO, the EPSO algorithm enhances exploration capabilities by avoiding stagnation on search space boundaries. A comparative analysis with the original PSO-based model (PSO-NPE), where nodes adopt maximum power for connectivity, reveals superior performance by EPSO-NPE. The enhanced model exhibits heightened energy-saving capabilities, ultimately extending the network's lifetime.**

***Index Terms*—IoT, Power estimation, PSO, Transmission power reduction, WSN.**

I. Introduction

Nowadays, the Internet of Things (IoT) is one of the extensive areas that allow data collection and sharing, and it is rapidly engaging our daily life (Abdalkafor and Aliesawi, 2022) (Gardašević et al., 2020). Mainly, the advanced technologies involving smart sensors, advanced communication technologies, and internet protocols are the critical elements of enabling IoT (Mohammed et al., 2024; Haseeb et al., 2020; Al-Rami and Alheeti, 2022). The number of connected devices to the IoT environment is growing (Al Zakitat et al., 2023; Abdaljabar, Ucan and Alheeti, 2021). It depicts a vast global network of thousands of physical machine devices around the world connected to the internet, collecting and sharing data and interacting with each other (Abdul-Qawy, Almurisi and Tadisetty, 2020). Thus, it has a significant impact on several sectors such as medical, industries, agriculture, home automation, and smart cities environments (Tao et al., 2024; Rani et al., 2020; Nafea et al., 2024). Furthermore, the establishment of IoT-based mesh networks and sensor nodes is dramatically increased, which is the issue that inherits the problem of energy constraints depicted by the transmission power of the network's nodes (Wasmi et al., 2021; Hamdi, Rashid and Nafea, 2024). Thus, network clustering and beamforming have been used to avoid inefficient transmission power (Heinzelman and Younis, 2000; Khediri et al., 2021; Ismael et al., 2023). However, the evolution of the IoT leads to remain this field an open area for more required correlated research.

Consequently, the power supply charge powers the three distinct subsystems: the sensor unit, the central processing unit, and the communication unit (Abdelaal and Theel, 2014; Haseeb et al., 2020). On another side, the mitigation of wasting power of a particular sensor node can be accomplished by several wireless node events such as packet overhead, overhearing, collisions, idle listening, and state transitions. This research aims to continuously link each of all of the nodes that are sensors in one cluster without triggering any state changes by the ideal amount of transmission power for each node in the network. At this time, we will not consider the other instances of energy waste. While switching between states would use up some of the battery

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life of the sensor, it could also be a way to conserve power. To save energy, the nodes can enter a sleep state and disable most of their functions (Mendes, Rodrigues and Chen, 2010; Del-Valle-Soto et al., 2020). The focus of this research is on network connectivity, therefore various node statuses will not be handled. The next step for stationary sensors is to gain network connectivity, subsequently, the goal of the network may change to a different mode.

Despite, calculating the least power level for each node placed on the network edge to connect its closer neighboring, or a group of nodes to reach the edges, in the case of the intermediate nodes, would be the ideal solution to detect the minimum required power to connect every wireless sensor network (WSN) node. As the node number in the cluster increased, finding out the closest neighboring nodes while maintaining the entire network connection would cause an elevation in computational overhead. For that, a sub-ideal solution, with a minimal computing-intensive might be utilized.

The particle swarm algorithm (PSO) algorithm is the most popular swarm-based algorithm used by several studies of WSN and energy estimation (Sun et al., 2020). This algorithm was proposed by Eberhart and Kennedy (1995) to cope with the non-linear functions with optimization issues. The PSO algorithm has become a widespread technique utilized to solve optimization issues in WSNs because of its simplicity and ability to provide high-quality solutions and fast convergence (Kulkarni and Venayagamoorthy, 2010; Ling et al., 2020). Thereafter, utilizing a PSO for power estimation is one of the potential solutions. However, the PSO algorithm is easy to dive into local optima, Thus, the model would neglect to get the correct results and bring about premature convergence. Consequently, this study sheds light on this issue and proposes an enhanced particle swarm optimization (PSO) for node power estimation named EPSO-NPE. This algorithm avoids the local optima problem to some extent by avoiding the stuck on the boundaries that occur in the original PSO and at the same time, it is supposed to enhance the exploration and exploitation procedure of the algorithm. The rest of the paper is structured as follows; Section 2 provides a literature review related to the proposed system and related methods and technologies. Therefore, Section 3 depicts the methodology of this study, while sections 4 provide the results of the taken experiments. Finally, Sections 5 and 6 provide discussion and conclusion, respectively.

II. Literature Review

A. WSN Clustering and Energy Consumption

Recently, WSNs have obtained the researcher's attention in many disciplines (Afsar and Tayarani-N, 2014) (Mohapatra et al., 2020). WSNs have originated as a new robust paradigm that can be utilized in lots of applications for generating various types of parameter reports, such as pressure, temperature, light, chemical activity, and humidity (Tyagi and Kumar, 2013; Khalifeh et al., 2021). Therefore, the WSN system can be assessed based on several parameters including, (i) the lifetime of a network, in which every network node has to be designed to control the local energy supply to get the maximum limit of network lifetime. (ii) Network Coverage, in which network nodes must be effectively distributed in all monitored areas to hit the coverage standards. (iii) Scalability in which it is supposed that any potential addition of new nodes to the network in the future must not cause any change in the network performance. (iv) Response time, in which the WSNs should respond to alarm-oriented risk situations like fire detection timely and quickly, and (v) Security, which is considered as one of the crucial measures of the WSNs, especially if the WSN is designed for security-oriented purposes (Mahajan and Dhiman, 2016; Mohapatra et al., 2020).

Therefore, to enhance the effectiveness of WSNs and increase network lifetime, energy efficiency, and scalability, as well as decrease routing delay, clustering is applied to WSNs (Afsar and Tayarani-N, 2014; Mahajan and Dhiman, 2016; Mohapatra et al., 2020). Clustering refers to dividing the network nodes into sets based on particular mechanisms (Afsar and Tayarani-N, 2014) (Mohapatra et al., 2020). In clustering, a group of nodes composed the clusters, some nodes are chosen to be cluster-heads and other nodes are called regular nodes. The cluster head (CH) receives data from regular nodes. Then, CH collects data and transmits them to the base station (Afsar and Tayarani-N, 2014; Ilyas et al., 2020). As clusters in WSN aid in data aggregation, this could assist in decreasing the energy consumption and transmission overhead (Mohapatra et al., 2020), Fig. 1 shows the flow of data in a networked cluster.

On another side, there are some design challenges associated with WSN clustering, include (i) Storage, in which sensors have storage limitations that can lead to some constraints on satisfying the query and storage requirement. (ii) Security, in which WSNs may incur too many threats and security issues that lead to the need to provide security protocols and measures. (iii) Communication, which should cover the entire WSNs area to maximize reliability and also enhance network coverage. (iv) Limited Energy, which is one of the most crucial challenges, where the energy forms a constraint to the sensor networks. Thus, decreasing the consumption of energy is one of the critical clustering

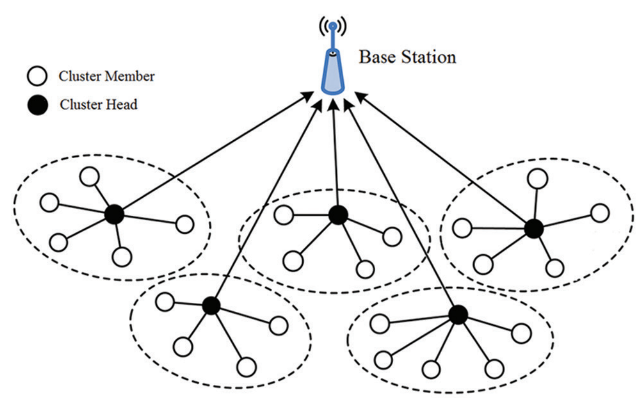

Fig. 1. Network Architecture of Clustered WSNs (Gui, Zhou and Xiong, 2016).

issues. (iv) Network Lifetime, in which one of the clustering design concerns is represented in the possible limitations of a network lifetime, while the sensor node is a low amount of energy. (vi) Quality of service (QoS), whereby quality is an important issue regarding clustering. Occasionally, clustering concentrates on energy efficiency rather than quality which can cause some clustering obstacles (Vyas and Chouhan, 2014; Mohapatra et al., 2020; Khediri et al., 2021).

Consequently, based on the aforementioned challenges, energy efficiency represents an important measure of WSNs' effectiveness. Hence, researchers proposed numerous protocols and approaches that may help in enhancing the energy consumption in clustering WSNs. Sensors can be split into several small sets named clusters to support the aggregation of data through an efficient network organization (Younis, Krunz and Ramasubramanian, 2006; Mohapatra et al., 2020). Thus, it would cause reliability enhancement, decrease the network communication overhead, and lead to considerable savings in energy. On another side, some Authors utilized clustering to select a group of network nodes. They institute an effective topology for prolonging the lifetime improve energy saving of battery-powered WSNs (Abd Aziz et al., 2012; Khediri et al., 2021).

B. PSO

PSO is an optimization algorithm inspired biologically by birds' social behavior or fishes' swarms and their ability to exploit or explore a d-dimensional search area for shelter or food (Jain and Sharma, 2013; Rao, Jana and Banka, 2017; Freitas, Lopes and Morgado-Dias, 2020). In a d-dimensional area, the PSO algorithm finds the optimal solution for a specific issue by utilizing an iterative operation (Kaur and Kumar, 2018; Freitas, Lopes and Morgado-Dias, 2020). In PSO, the swarm is formed of a group of individual particles. Each particle in the swarm owns a specific fitness measured by the fitness function. The particle is (flown) over the d-dimensional search area (Rini, Shamsuddin and Yuhaniz, 2011; Freitas, Lopes and Morgado-Dias, 2020). The particles interact with each other, constituting a particular social behavior. The particles are estimated regarding their fitness function, and then their speeds and positions are updated in every step of the PSO algorithm. Each particle's role and rate are updated based on its experience and the neighboring particles. The superior work might be the minimum or maximum values. The updates of particles depend on the tracking of two extreme values. The first one is the best (optimal) solution of the (individual extremum pbest) particles. The second is the best (optimal) solution for the whole population, called the (global extremum gbest). Therefore, several parameters control the searching behavior of the PSO algorithm including (i) coefficient of inertia weight w, which controls the algorithm's tendency to expand search space and explore new areas within it. (ii) accelerate constants c_1 and c_2, in which it functions as the weight of accelerating statistically when each particle is forwarded to the position of pbest and gbest, (iii) and r_1 and r_2, which are random numbers between [0,1]. In the original PSO algorithm, the updating equations of the particle's velocity and position are as follows:

$$v_i^{t+1} = w^t v_i^t + c_1 r_1^t \left(p_{ibest}^t - x_i^t \right) + c_2 r_2^t \left(gbest - x_i^t \right) \quad (1)$$

$$x_i^{(t+1)} = x_i^t + v_i^{(t+1)} \quad (2)$$

Where t represents the number of iterations, v_1 represent the speed of the particle and x_i is the position of the particle.

In literature, several studies addressed some issues related to WSNs designation, such as energy constraint, limited capabilities, and bandwidth unavailability, and generally routing protocol optimization. Thus, the issue can be modeled as an optimization problem, which allows metaheuristic algorithms to be used in their solution. From a central point of view, several studies produced the PSO algorithm as an optimization solution in WSNs. Some of these studies examined the optimization algorithms such as the PSO algorithm functioning to reduce the energy consumption of WSN, enhance the convergence of WSN, and increase its lifetime. Next are some related studies that were reviewed.

A study by da Silva Fré et al., (2015) utilized PSO to calculate the nodes' transmission powers in related areas of a WSN. This work's findings indicated that the suggested PSO algorithm allowed the saving of sensors' energy significantly by at least, 1 dBm of the overall transmission power of the network compared with a simplistic method. Meanwhile, Rao, Jana, and Banka proposed an approach consisting of a combination of energy-efficient CHs selection and PSO (PSO-ECHS). This approach takes various parameters into account as the sink distance, intra-cluster distance, and sensor nodes' residual energy. The findings affirmed the suggested approach's superiority compared with the other existing approaches regarding the network lifetime and energy consumption. As they could run the algorithms by changing the sensor node number from 300 to 500, CHs number from 30 to 50, and calculated overall consumption of energy at the end of 5000 rounds.

Kaur and Kumar, (2018) have utilized the PSO-UFC protocol to handle the imbalance of inter-cluster and intra-cluster energy consumption between Master CHs. The simulation results manifested that the proposed protocol increases the lifetime of the network and enhances energy consumption. In the FND criteria, the used protocol enhanced the network lifetime by 86%, and in the HDN criteria the network lifetime was enhanced by 68%. In addition, Latiff, Tsimenidis and Sharif, (2007) proposed PSO-C as an energy-aware clustering algorithm for WSN. The proposed approach operated to select the best (k-CHs) that can reduce the cost through routing. The approach was a centralized and distance-based approach that takes into consideration the extreme distance between CH and other nodes and the residual CH candidates' energy. Nodes with adequate energy are chosen to be CHs, while nodes with an energy higher than the average are qualified to be a CCH in each round.

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On the other hand, Tam et al., (2018) suggested an algorithm based on PSO and fuzzy clustering to minimize network energy consumption and decrease network disconnects. The proposed model resolved the clustering limitations of 3D WSN. Moreover, fuzzy clustering enables more easily to determine the optimal structure of clustering in 3D WSN. Meanwhile, Wang, (2020) applied PSO for optimizing the deployment of WSN nodes. The results revealed that PSO could optimize WSN layout optimally and effectively, coped with the fixed sensor nodes' impact on optimization, realized rapid convergence speed, and enhanced the efficacious WSN coverage.

Furthermore, a study by Jain and Sharma, (2013) sought to solve the coverage issues in distributed WSN. Whereby, they proposed a modified discrete binary PSO algorithm for the WSN nodes' placement to obtain the maximum coverage. The proposed algorithm fixed the coverage problem by setting a finite sensor number, optimizing the sensor's deployment, and considering the sensor deployment scheme factor. On another side, Sahoo, Amgoth and Pandey, (2020) integrated the PSO algorithm with the energy-efficient clustering and sink mobility (ECSM) technique to address the sink mobility and cluster head (CH) selection issues. This study covered the node degree, residual energy distance, and energy consumption rate (ECR) as CH selection factors. The results indicated that the PSO-ECSM enhanced the stability period and improved the network's lifetime and throughput.

III. Methodology

A. The System and Network Connectivity

This research only considers scripts that have one cluster and N wireless sensors. Using the newly formed mesh network, they must transmit measurement packets to a sink node. This means that an L-sided square would contain the locations of the sinks and sensors. In addition, the subsequent calculation of the global neighbors' matrix Γ_γ is based on the transmitted power vector γ, as expressed in equation (3):

$$r_{ij}(\gamma)=\begin{cases}0, if\ P_j < P_{th}\\ 1, if\ P_j \geq P_{th}\end{cases} \quad (3)$$

where P_j is the power which it is received at node j, when i is transmitting with a power γ_i, and P_{th} is representing the sensitivity of the receiver. Therefore, a connection is established between two nodes when the first node broadcasts a strong enough signal to exceed the sensitivity of the receiver. According to Fig. 2, the distance from the node is depicted by the circles at its center, and the measured power is precisely P_{th}. This indicates that its signal can be received by another node within the circle.

Moreover, according to the Friis formula, equation (4), There is a direct correlation between the received power and both the transmitted power and the physical distance between the nodes:

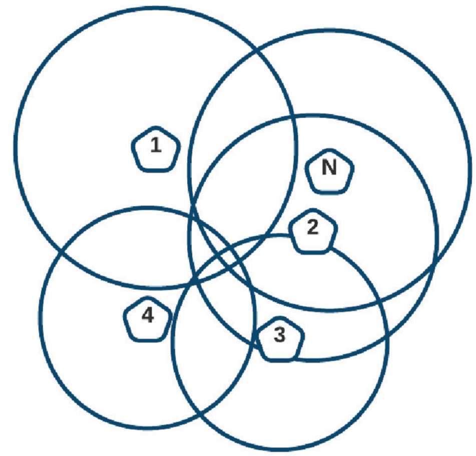

Fig. 2. Structure model.

$$\frac{P_R}{P_t}=\frac{A_r\,A_t}{d^2\,\lambda^2} \quad (4)$$

Where, P_R stands for the received power, P_t for the transmitted power, d for the transmitting and receiving antenna's effective areas, and λ for the wavelength, which is acquired by dividing the light's speed c by the frequency f of the signal. The focus of this work is therefore on a power transfer optimization model rather than a particular hardware architecture of sensor nodes. Therefore, to represent the effective antenna regions, the simplest possible antenna model would be chosen. Accordingly, the following are the effective areas given by equation (5) when each sensor node is equipped with a single isotropic antenna for transmission and reception:

$$A_{isotropic}=\frac{\lambda^2}{4\pi} \quad (5)$$

And making $A_r = A_t = A_{isotropic}$, the power ratio (i.e., equation 4) simplifies to equation (6) as follows:

$$\frac{P_R}{P_t}=\left(\frac{\lambda}{4\pi d}\right)^2 \quad (6)$$

Furthermore, after computing the neighbors matrix using equation 3, to find out whether the network is linked or not, a method is employed. When each of the nodes in a network possesses at least one link to each other and can form a path that includes all of the nodes, we define it as a fully connected network.

Determining the fully connected condition of a particular network is harder when the number of nodes is large, but easier when a network has a smaller number of nodes or/and a smaller AoI. Whereby, in the first case, a large number of nodes linked in one network makes its management essential. When determining connectedness, the initial step is to compute the Laplacian Matrix of the neighboring matrix, which is provided by equation (7) where n_i is the i^{th} node and n is the total number of nodes (GROSS, 2004).

$$L = (l_{ij})_{n\times n} \tag{7}$$

$$l_{ij} = \begin{cases} deg(n_i) & if\ i = j \\ -1\ if\ i \neq j\ and\ \Gamma_{ij} = 1 \\ 0 & otherwise \end{cases} \tag{8}$$

where $deg\ (n_i)$ is the number of connected nodes to the node n_i, and this value can be determined using equation (9), as shown below:

$$\deg(n_i) = (r^2)_{ij} \leftrightarrow i = j \tag{9}$$

Therefore, for $i=j$, the number of connections to n_i is the same as the square of the neighbor matrix. Determining the eigenvalues ψ of the Laplacian matrix L, using equation (10), is the second step after calculating the Laplacian matrix. The process is as follows:

$$L.E = \psi.E \tag{10}$$

where E is an eigenvector, which is a column vector with n elements that have to be equal to and match every possible Laplacian eigenvalue ψ. The eigenvalues linked to each eigenvector are the values of ψ that satisfy equation (10) and can be set up inside a vector ψ in the following way:

$$\Psi = [\psi_1, \psi_2, \psi_3, \ldots, \psi_n]^t \tag{11}$$

with $\psi_1 < \psi_2 < \psi_3 < \ldots < \psi_n$

The fully connected requirement can only be met if the second smallest Laplacian eigenvalue ψ_2, also known in the Neighbor Matrix as the algebraic connectivity, is positive. Finally, in the neighbor matrix, there must be a positive second smallest Laplacian eigenvalue and a minimum of one connection per node to determine if a network is fully connected. Under these conditions, a fully connected cluster can be initiated using the transmission power of individual nodes (Wormald, Gross and Yellen, 2004).

B. The EPSO-NPE Model

In this study, the EPSO-NPE model is proposed. In the original PSO algorithm, the algorithms start with the exploration task and then further for the exploitation task depending on the particle's speed. However, in the velocity and position update equation, if a particular particle exceeds the velocity or/and its position out of boundaries, the algorithm forces the particle to determine boundaries where the particle is mostly stuck on there. Thus, this behavior is considered as one of the main reasons behind the degradation in local optima of the original PSO algorithm. The node power estimation based on PSO is as Algorithm 1.

Consequently, to solve this problem and enhance the PSO, the particle involved on out of velocity bounds problem takes a new value of velocity within the velocity range as following equation 1:

$$P_{out}^{v} = (v_{up} - v_{low}) \times rand(1,1) + v_{low} \tag{12}$$

Where v_{up} and v_{low} are the maximum and minimum limits of velocity.

Algorithm 1: PSO-NPE

```
Initialize algorithm's parameters include c1, c2; the value of inertia weight
ωmin, ωmax, the maximum number of iterations, the population size Pop and
the, lower bound lb, upper bound ub, and minimum velocity Vmin, maximum
velocity Vmax.
for i∈{1,2,…., N} do
x_i←rand (lb, ub)
v_i←rand (Vmin, Vmax)
endfor
for i∈{1,2,…., Pop} do
fitness_i←f (x_i, position_script)
f(pbest)_i ← fitness_i ▷ individualfitness
pbest_i←x_i
endfor
for(gbest) ← min)f(pbest))▷ globalfitness
gbest←pbest
ω←ω*ωdamp
for t∈{1,2,…., t_max} do
for i∈{1,2,…., N} do
according to Equation (1) update the speed of particle i
for j∈{1,2,…., N} do
if (v_ij>vMax)
(v_ij←vMax)
endif
if (v_ij<v Min)
(v_ij←vMin)
endif
endfor
endfor
for i ∈{1,2,…., N} do
according to Equation (2) update the position of particle i
for j ∈{1,2,…., N} do
if (x_ij>xMax)
(x_ij←xMax)
endif
if (x_ij<xMin)
x_ij←xMin)
endif
endfor
endfor
for i ∈{1,2,…., N} do
fitness_i←f (x_i, position_script)
if (fitness_i<f (pbest_i)) then
f (pbest)_i←fitness_i
pbest_i←x_i
endif
if (f (pbest_i)<f (gBest)) then
f (gbest)←f (pbest)_i
gbest←pbest_i
endif
endfor
endfor
Output optimal solution by gbest.
```

Meanwhile, the particle involved in the position out of bounds problem is updated to a new position within the search space range as in the following equation 2:

$$P_{out}^{pos} = \left(pos_{up} - pos_{low}\right) \times rand(1,1) + pso_{low} \quad (13)$$

To implement the proposed model, the algorithm's parameters were set as follows; population size set to 30, in which each particle presents a solution for its corresponding transmission power of a node. Learning coefficients *c1* and *c2* are set at 2, and the value of inertia weight *ω* and inertia weight damping ratio are set to 1 and 0.7, respectively. The maximum number of iterations is set to 100, and the population size *Pop* is set to 20. Finally, the lower bound *lb* and upper bound *ub* are set to −30 and 0, and minimum velocity *Vmin*, and maximum velocity V*max are set to -4 and 4, respectively*, as illustrated in Table I.

Therefore, the PSO algorithm according to the fitness function will decide whether all nodes are associated with the estimations of the transmission power of every node. In the event of all nodes connection, then the fitness function restores the amount of the power of the nodes. Otherwise, it restores a limitless value represented by an infinite value. The pseudocode of this technique is illustrated in Algorithm 2. The next section provides the experimental results. Moreover, the node transmitted power estimations that outcomes in the smallest amount (i.e., energy saving), is acquired from the stored gbest values.

Algorithm 2: EPSO-NPE

Initialize algorithm's parameters include *c1*, *c2*; ωmin, ωmax, the maximum number of iterations, the population size *Pop* and the, lower bound *lb*, upper bound *ub*, and minimum velocity *Vmin*, maximum velocity V*max*.
for I ∈ {1,2,…., *N*} *do*
x_i←*rand* (*lb*, *ub*)
v_i←*rand* (*Vmin, Vmax*)
endfor
for i ∈{1,2,…., *Pop*} *do*
$fitness_i \leftarrow f(x_i, position_{script})$
$f(pbest)_i \leftarrow fitness_i \triangleright individualfitness$
$pbest_i \leftarrow x_i$
endfor
for (*gbest*)←min) *f* (*pbest*))⊳*globalfitness*
gbest←*pbest*
gbest←*pbest*
ω←*ω***ωdamp*
for t ∈{1,2,…., t_{max}} *do*
for *i* ∈{1,2,…., *N*} *do*
according to Equation (1) update speed of particle *i*
for j∈{1,2,…., *N*} *do*
if (v_{ij}>*vMax*) or (v_{ij}<*vMin*)
according to Equation (12) update speed of particle *i*
endif
endfor
endfor
for i ∈{1,2,…., *N*} *do*
according to Equation (2) update the position of particle *i*
for j ∈{1,2,…., *N*} *do*
if (x_{ij}>*xMax*) or (x_{ij}<*xMin*)
according to Equation (13) update speed of particle *i*
endif
endfor
endfor
for i ∈{1,2,…., *N*} *do*
$fitness_i \leftarrow f(x_i, position_{script})$
if ($fitness_i < f(pbest_i)$) then
$f(pbest)_i \leftarrow fitness_i$
$pbest_i \leftarrow x_i$
endif
if ($f(pbest_i) < f(gBest)$) then
$f(gbest) \leftarrow f(pbest)_i$
$gbest \leftarrow pbest_i$
endif
endfor
endfor
Output optimal solution by gbest

IV. Results and Discussion

This section provides the results of the performed experiments. The transmission power optimization was performed one by implementing the original PSO-NPE method that is illustrated in Algorithm 1, and the other one is by implementing the proposed method (i.e., EPSO-NPE) that is illustrated in Algorithm 2. Moreover, to get a robust result, the algorithms were run 10 times for each. The algorithms were tested over 15 scripts, each script includes the transmitter and receiver positions of 20 nodes, in which the area of random sensors distribution is identified to 20×20 length of meter, and sensor sensitivity and transmission frequency are −60 dbm and 915 MHz, respectively.

Fig. 3 illustrates the summation of the transmission power of nodes for 15 taken scripts by the PSO-NPE and EPSO-NPE methods. Generally, the graph shows that the estimated power determined by the proposed method is less than the one determined by the PSO-NPE over all 15 scripts. Moreover, it is clear that in script 8 the PSO-NPE failure to provide a solution, while the EPSO-NPE succeeded to provide a solution with approximate power -4.95dBm. This indicates that the proposed algorithm (i.e. EPSO) has a higher capability to search the search space and find a solution compared with the original PSO. On another side, it can be observed that in comparison with PSO-NPE, the use of EPSO-NPE has saved, at minimum, approximately 1dBm of power, and at maximum approximately 2 dBm of Power as it can be seen in script number three.

On another side, Figs. 4 and 5 illustrate the distribution of the estimated power values and the medians, for the undertaken 15 scripts by PSO-NPE and EPSO-NPE, respectively. Regardless of the difference between the boxes resulting from the same method. Comparably between the two methods, the box plots for PSO-NPE are lower than the

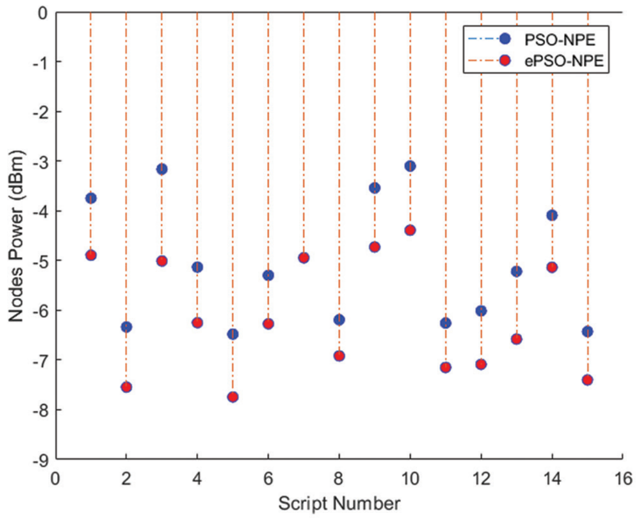

Fig. 3. Nodes power estimation for the PSO-NPE and EPSO-NPE methods.

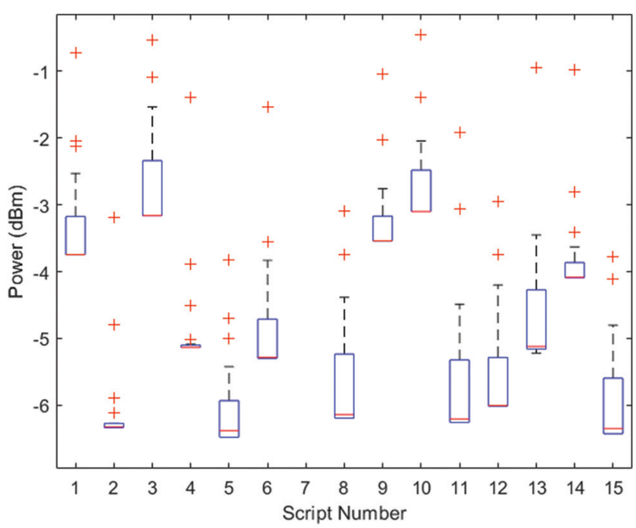

Fig. 4. Nodes powers by each script using PSO-NPE.

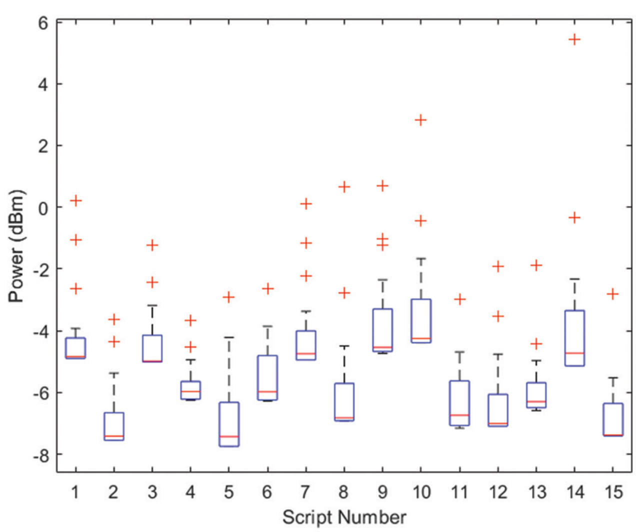

Fig. 5. Nodes powers by each script using EPSO-NPE.

TABLE I
Parameter/Factor Setup of PSO and EPSO

Parameter/Factor	value
Population size	20
Dimension	20
Iterations	1000
runtime	10
C1	2
C2	2
ωmin-ωmax	0.4, 0.9
Vmin- Vmax	-4, 4
lb-ub	-30, 0

equivalent plots for EPSO-NPE over all scripts. Moreover, node power estimations based on the EPSO-NPE are much lower than the PSO-NPE within several scripts such as in script 3 and script 5. On another side, it can be observed that some of the box plots regarding PSO-NPE are short compared with the ones by the EPSO-NPE, such as in scripts 2, 4, and 14. This indicates that there is an obvious difference between the two methods' performances, where the latter outperforms the one by the original PSO in which, unlike the EPSO, the overall estimated power based on PSO has a high level of agreement over all iterations. As a result, this is sufficient evidence that proves the better exploration ability of the proposed method.

V. Conclusion

This paper proposed a new method named as EPSO-NPE to enhance the performance of the node transmission power estimation, thus to save the energy of sensor nodes within the connected state. Consequently, compared with the method based on the original PSO, the use of EPSO-NPE has saved, at minimum and maximum 1dBm and 2dBm, respectively, of the total transmitting power of the network. Moreover, unlike the PSO-NPE, the EPSO-NPE could provide superior solutions for all the scripts. As a result, the outperforming of the proposed method could be proven by several results, and this superior performance I showed overall undertaken scripts. Moreover, while the exploration behavior of the algorithm is boosted, the proposed EPSO algorithm has proven a better searching ability with high exploration and exploitation capabilities. For future work, more empirical analysis will be established on node placements and its power, and with a higher number of scripts. Technically, more studies will be established on the PSO algorithm and the possibility to enhance its performance from other aspects, and extend the comparison range to evolve more methods, techniques, and other frequencies such as ZigBee and WiFi.

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