

INERTIA PARTICLE SWARM OPTIMIZATION WITH DYNAMIC VELOCITY BASED CLUSTERING TECHNIQUE IN WIRELESS SENSOR NETWORKS

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ABSTRACT. Wireless Sensor Networks (WSN) comprises a collection of nodes commonly employed to observe the physical environment. Different sensor nodes are linked to an inbuilt power unit to carry out necessary operations and data transmission between nearby nodes. The maximization of network lifetime and minimization of energy dissipation are considered as the major design issue of WSN. Clustering is a familiar energy efficient technique and the choice of optimal cluster heads (CHs) is considered as an NP hard problem. This paper presents an Inertia Particle Swarm Optimization algorithm with dynamic velocities (IPSO-DV) algorithm based clustering technique in WSN. The aim of the IPSO-DV technique is to select the CHs in such a way to maximize network lifetime. The IPSO-DV algorithm derives a fitness function (FF) to select CHs using distance to BS and remaining energy level. The application of dynamic velocities helps to improvise the effectiveness of the conventional PSO algorithm. To assure the performance of the presented IPSO-DV algorithm, a series of experiments were carried out and the results are investigated under several aspects. The experimentation outcome ensured the effective performance of the IPSO-DV algorithm over the compared clustering techniques.

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2020 *Mathematics Subject Classification.* 68M18.

Key words and phrases. Clustering, Energy efficiency, PSO algorithm, Network lifetime, Metaheuristics.

Submitted: 20.12.2020; *Accepted:* 06.01.2021; *Published:* 21.01.2021.

1. INTRODUCTION

Recently, Wireless Sensor Network (WSN) plays a vital role in different fields and gained massive researchers because of their complex, multifaceted demands that prominently divulge inherent trade-offs. A WSN is configured with sensor nodes which are linked by an ad hoc as well as self-configuring connection. It is composed of a collection of spatially distributed independent sensors for monitoring the ecological attributes like temperature, pressure, moisture, humidity and so on and convey the information by a network to basic position named as sink or Base Station (BS). Based on the applications, diverse classes of sensor nodes are used for observing attributes like humidity, temperature, sound, movement of objects, and so forth. The model of WSNs shows massive limitations as there are minimal resources with respect to memory space, computation as well as exchanging messages. Theoretical evaluation cannot be more accurate under various cases for predicting and preventing the damage of sensors. The model complexity of WSNs enhances with the new applications and the demands. Traditional models have developed ad hoc networks which are inadequate to cater the requirements of sensor applications and it makes novel procedures and protocols have to be defined. Clustering [1-3] is a method that isolates the geographical region as tiny sectors. It assists the sensor nodes to share the overhead for all server nodes uniformly and a node is allocated as head of a cluster, termed as 'Cluster Head' (CH). The cluster contains a CH with massive cluster members (CM). The role of CH is that, it has to incorporate the nodes involved in clusters [4-5]. Therefore, appropriate CH elections [6-7] with best potentials are essential for managing the network's energy-efficiency. However, the meta-heuristic methods as well as Computational intelligence (CI) methodologies were applied to cluster for resolving the NP-hard optimization problem. Mehra et al. [8] projected a Fuzzy-Based balanced cost CH Selection method (FBECS) which is composed of residual energy (RE), distance as well as node density is fixed as input to Fuzzy Inference System (FIS). To select an optimum set of CHs, the Eligibility index should be calculated for all images. The concerned protocol has ensured load balancing by the election of best candidates to perform coordination in cluster.

2. THE PROPOSED IPSO-DV ALGORITHM

Fig 1 shows the working process of IPSO-DV model. Once the nodes are deployed and initialized, BS executes the IPSO-DV algorithm to determine the CHs. Here, PSO is defined as a population-aided optimization model. The arbitrary solutions of these modules are initiated with a population and find best solutions in all generations. A swarm is composed of a collection of particles

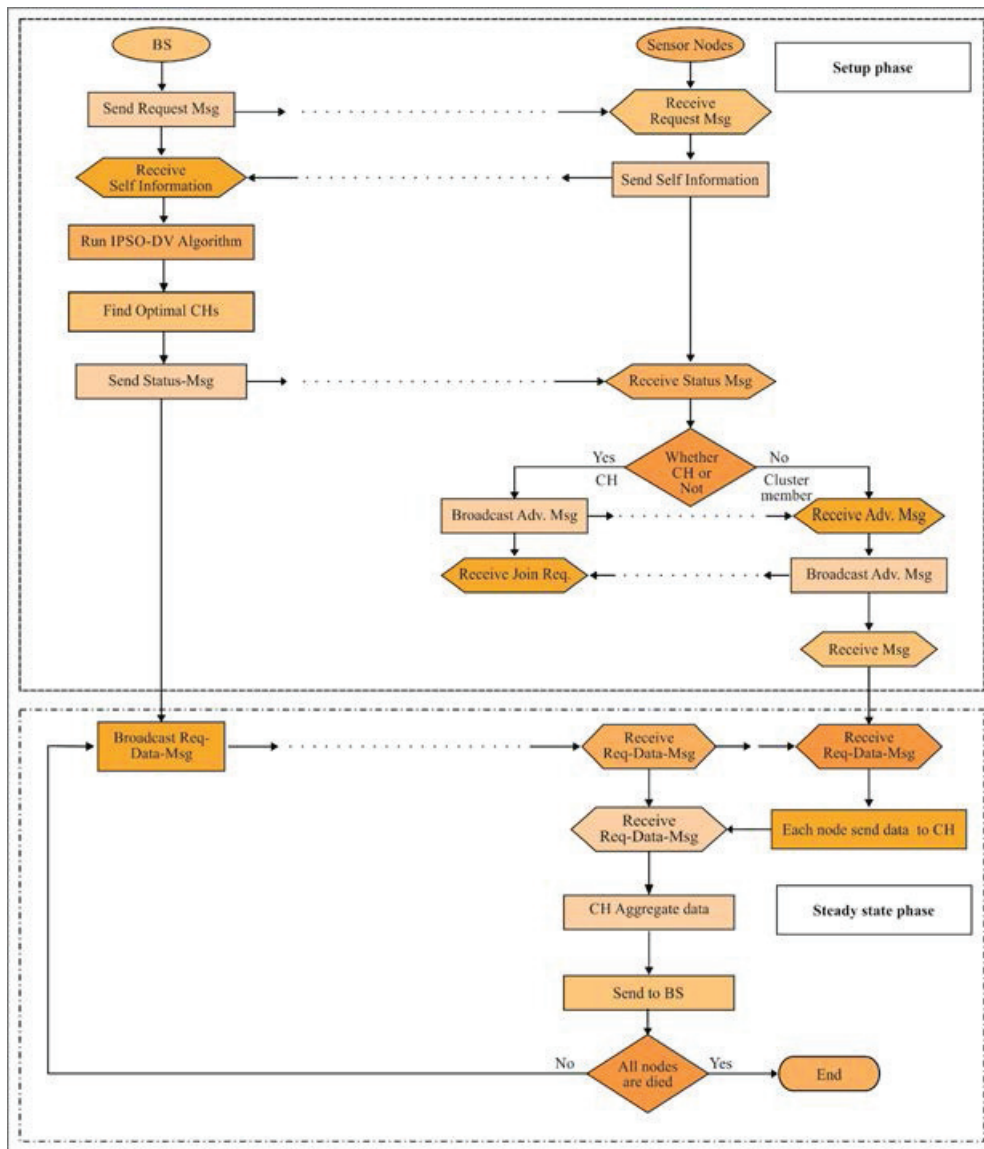


FIGURE 1. Working Process of IPSO-DV model

moves inside the search area; it represents a significant solution. In a physical n -dimensional search space, the position and velocity of all particles i are exhibited as vectors $X_i = (x_{i1}, \dots, x_{in})$ and $V_i = (v_{i1}, \dots, v_{in})$, correspondingly. Exploring the principles by PSO depends upon predefined mechanism which is defined in the following. A flock of agents has optimized specific objective function. These individuals are composed of optimal values Pbest and corresponding position. Additionally, the individual has higher value in a group Gbest among pbest. Consider the $Pbest_i = (x_{i1}^{pbest}, \dots, x_{in}^{pbest})$ and $Gbest_i = (x_{i1}^{gbest}, \dots, x_{in}^{gbest})$ as the location of individual i and its neighbor's optimal position. With the application of this objective, the altered velocity of individual is determined under the employment of recent velocity and distance from Pbest and Gbest as shown in

$$(2.1) \quad V_i^{k+1} = \omega V_i^k + c_1 rand_1 \times (Pbest_i^k - X_i^k) + c_2 rand_2 \times (Gbest_i^k - X_i^k),$$

where V_i^k implies present velocity of individual i at iteration k , V_i^{k+1} changed the velocity of individual i at iteration $k+1$, X_i^k present position of individual i at iteration k , ω refers the inertia weight parameter, c_1, c_2 defines the acceleration factors, $rand_1, rand_2$: random value from 0 and 1, $Pbest_i^k$ shows optimal position of individual i till iteration k , $Gbest_i^k$ signifies the best position of a group till iteration k .

The individual travels from recent position to next one by changed velocity in (2.1) by applying the given expression:

$$(2.2) \quad X_i^{k+1} = X_i^k + V_i^{k+1}.$$

The parameters c_1 and c_2 depicts the collection of constant values. Lower values enable the individuals to move far away from target areas. Besides, higher measures result in immediate movement to defined regions. Thus, acceleration constants c_1 and c_2 are allocated as 2.0 while $rand_1$ and $rand_2$ implies arbitrary values, and it is uniformly distributed among 0 and 1. Such values are dissimilar for all iteration as it is produced in random manner regularly. The search process of PSO by applying the changed velocity and position of an individual i using Eqs. (2.1) and (2.2).

2.1. PSO with Dynamic Velocities. For enhancing the performance of the conventional PSO algorithm, dynamic velocities are applied. The new velocity of

IPSO-DV is updated as

$$v_{ij}(t+1) = \begin{cases} wv_{ij}(t) + c_1r_1(pbest_{ij} - x_{ij}(t)) + c_2r_2(gbest_j - x_{ij}(t)) & \text{if } r1 > 0.5 \\ \tau(v_{ij}(t) + c(P_{mj} - x_{ij}(t))) & \text{otherwise} \end{cases},$$

where v_{ij} determines the velocity of particle i in the dimension j at the t^{th} generations, $r1$ and $r2$ represents the uniform random numbers within the range of $[0,1]$, $c1$ and $c2$ determines the cognitive and social coefficient parameters,

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times t,$$

where w_{max} , w_{min} are the higher and lower values of inertia weight:

$$\tau = \frac{2}{|2 - c - \sqrt{c^2 - 4c}|} \text{ and } c = c_1 + c_2, c > 4$$

and

$$P_{mj} = \frac{c_1 pbest_{ij} + c_2 gbest_j}{c}.$$

The position of the particle updated using the following equation:

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1).$$

A cluster is developed by BS or sink according to the centralized clustering. In case of clustering BS, the details are broadcasted as group of messages for the sensor nodes. Once the message is received by a sensor node, it forwards the node data like node ID, place (distance from BS in X and y position), energy-loss as well as energy loss ratio and recent energy to forward BS. The BS is invoked with following conditions as given below:

Step 1. Transformation of problem into PSO space where PSO particle is composed of 2D like particle position and velocity.

Step 2. Determining fitness value (FV) using fitness function. The newly develop FF for IPSO-DV technique is to normalize average distance and average

energy. The fitness score is measured for a particle with the help of given function:

$$\begin{aligned} \text{Fitness value} = Fv = & \alpha_1 \cdot \frac{(\sum_{i=0}^n d(\text{present node, member } i))}{n} \\ & + \alpha_2 \cdot \frac{(\sum_{i=0}^n E(\text{member } i))}{E(\text{present node})} \\ & + (1 - \alpha_1 - \alpha_2) \cdot \frac{1}{\text{No of members covered by current node}}, \end{aligned}$$

where α_1 and α_2 defines the weighing parameters and implies the count of members concealed inside a cluster.

Step 3. Producing novel particles from initial solution. Development of new particles from previous ones is a production of a new particle.

Step 3.1. Determination of new velocity (V_{new}): the present velocity is assumed as particle's positions which are modified. The novel velocity is measured by the following:

$$V_{new} = \omega^* V_{old} + w_1 (\text{pos}_{lbest} - \text{pos}_{cbest}) + w_2 (\text{pos}_{gbest} - \text{pos}_{cbest}),$$

where ω implies inertia weight and w_1 and w_2 refers fundamental PSO tuneable variables.

Step 3.2. Calculation of novel position of the particle as provided below:

$$\text{pos}_{new} = \text{pos}_{old} + V_{new}$$

At last, new particle is attained.

Step 4. Estimation of FV for novel particles. Fitness measures of new particles can be evaluated by applying FF in Step 2 with better velocity as well as new position.

Step 5. FV of previous particle and new particle are compared and optimal one is chosen for consecutive iteration:

If new FV > old FV

select new particle;

else

old particle is furthered to subsequent iteration.

Step 6. For all iterations, an optimal solution has been elected as lbest solution. The particle with higher FV in recent iteration is elected as lbest solution.

Step 7. The lbest solutions from each iteration of the particle where it has higher values among the solutions which decided as gbest solution. The last solution undergoes decoding as clusters.

3. PERFORMANCE VALIDATION

This section validates the effective performance of the IPSO-DV algorithm in terms of number of number of alive nodes, dead nodes, and network stability.

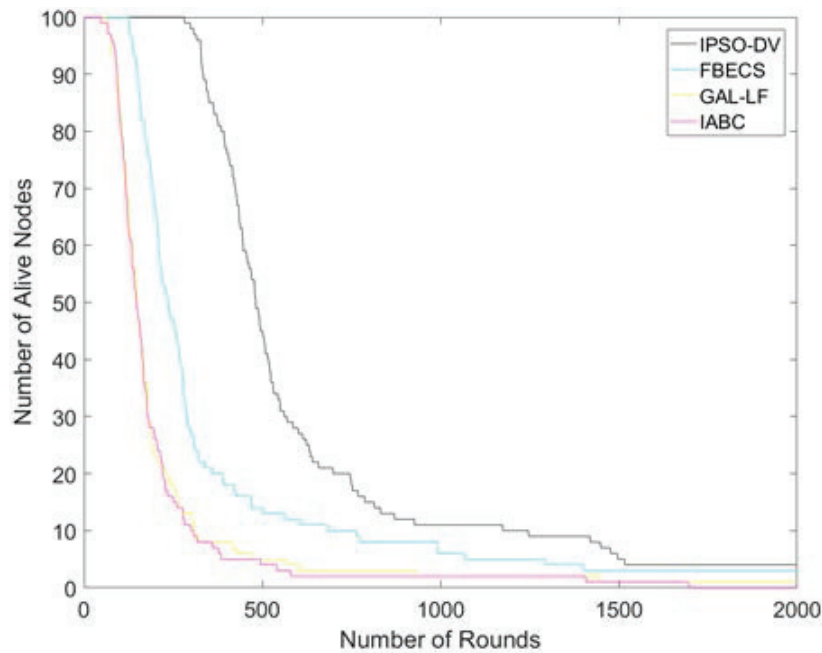


FIGURE 2. Alive node analysis of IPSO-DV algorithm under 100 node count

For comparison purposes, three methods are used namely FBECS, IABC, and GAL-LF. Fig 2 analyzes the alive node results of the IPSO-DV algorithm under 100 nodes. The figure exhibited that the IABC algorithm has shown inferior number of alive nodes compared to other techniques. At the same time, the

GAL-LF technique has demonstrated slightly higher number of alive nodes. Followed by, the FBECS algorithm has outperformed the IABC and GAL-LF algorithms by attaining a higher number of alive nodes. Fig 3 illustrates the dead

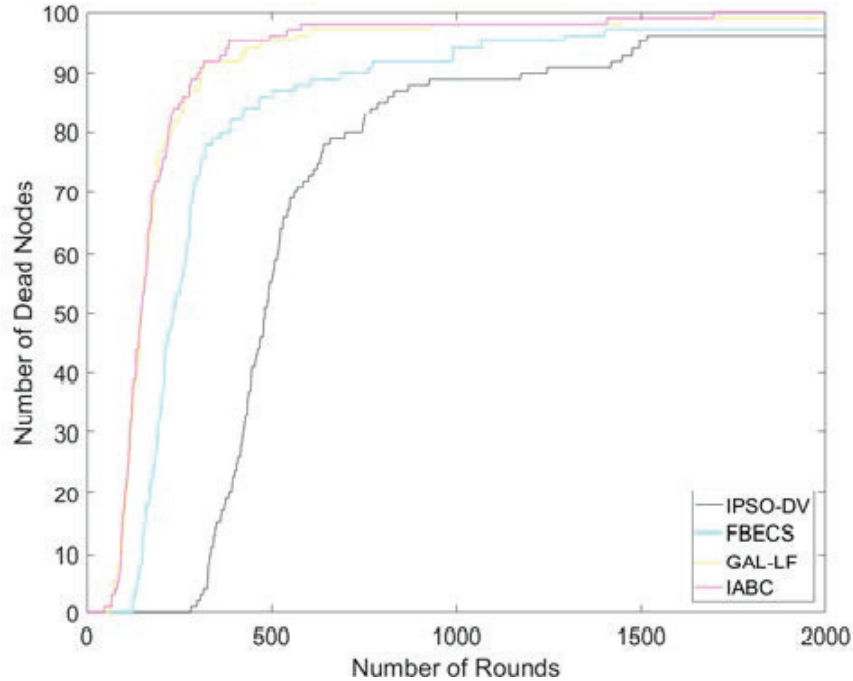


FIGURE 3. Dead node analysis of IPSO-DV algorithm under 100 node count

node analysis of the IPSO-DV algorithm under varying node count of 100. On analyzing the results, the IBAC algorithm has failed to achieve effective network lifetime by attaining maximum number of dead nodes. Followed by, the GAL-LF algorithm has tried to exhibit slightly effective results by achieving a slightly lower number of alive nodes. For instance, under the execution round of 1000, a maximum of 98, 97 and 95 nodes become dead by the IABC, GAL-LF and FBECS algorithms. Fig 4 depicts the analysis of the IPSO-DV algorithm with existing methods interms of number of packets transmitted to BS. The figure portrayed that the IPSO-DV algorithm has resulted to a higher number of packets transmitted to BS under varying number of nodes. Besides, the FBECS algorithm has shown slightly lower number of packets transmitted to BS over IPSO-DV algorithm.

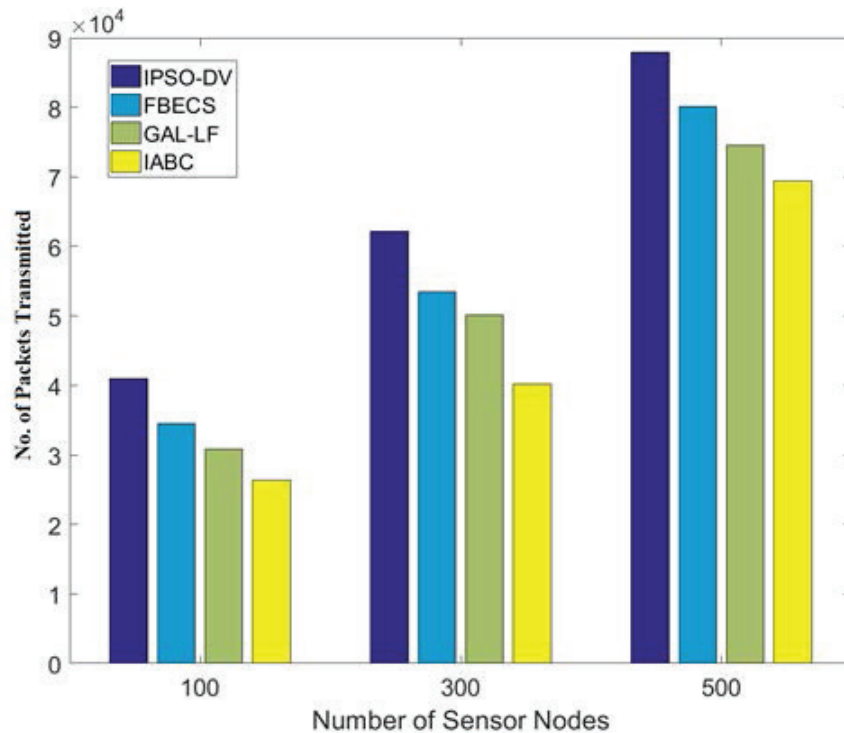


FIGURE 4. Analysis of IPSO-DV algorithm interms of number of packets transmitted to BS

4. CONCLUSION

This paper has developed a new IPSO-DV algorithm based clustering technique in WSN. The aim of the IPSO-DV algorithm is to select the CHs in such a way to maximize network lifetime. The proposed model operates on two phases, namely setup phase and steady state. At the setup phase, node deployment, node initialization, and neighboring data collection takes place. Then, the IPSO-DV algorithm has derived a FF to select CHs using distance to BS and remaining energy level. The application of dynamic velocities helps to improve the performance of the conventional PSO algorithm. Followed by, in the steady state phase, the nodes located closer to the selected CHs joins to it and forms cluster. At last, data transmission takes place from CMs to CHs and then it is forwarded to BS through multihop communication. The detailed simulation results ensured that the IPSO-DV algorithm has resulted to maximum network lifetime over the existing models.

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