Multiple Solutions Based Particle Swarm Optimization for Cluster-Head-Selection in Wireless-Sensor-Network

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***Abstract*—Wireless sensor network (WSN) has a significant role in wide range of scientific and industrial applications. In WSN, within the operation area of sensor nodes the nodes are randomly deployed. The constraint related to energy is considered as one of the major challenges for WSN, which may not only affect the sensor nodes efficiency but also influences the operational capabilities of the network. Therefore, numerous attempts of researches have been proposed to counter this energy problem in WSN. Hierarchical clustering approaches are popular techniques that offered the efficient consumption of the energy in WSN. In addition to this, it is understood that the optimum choice of sensor as cluster head can critically help to reduce the energy consumption of the sensor node. In recent years, metaheuristic optimization is used as a proposed technique for the optimal selection of cluster heads. Furthermore, it is noteworthy here that proposed techniques should be efficient enough to provide the optimal solution for the given problem. Therefore, in this regard, various attempts are made in the form of modified versions or new metaheuristic algorithms for optimization problems. The research in the paper offered a modified version of particle-swarm-optimization (PSO) for the optimal selection of sensor nodes as cluster heads. The performance of the suggested algorithm is experimented and compared with the renowned optimization techniques. The proposed approach produced better results in the form of residual energy, number of live nodes, sum of dead nodes, and convergence rate.**

***Keyword*— artificial intelligence, computation intelligence, metaheuristics, optimization, wireless-sensor-networks**

I. Introduction

Wireless sensor networks are employed in diverse applications, for instance; in the field of monitoring of an environment, disaster management, industrial process management, battlefield monitoring $etc.$ In WSN, the sensor node has the sensing and transmission capacity to sense the operational environment for the desired information and forward this data it to a base-station for further processing [1]. When the sensor node is installed, then it is not possible to access it for recharging or replace its battery. This means that the sensor node's energy is limited and this requires designing such a type of protocol (s) that supports the efficient utilization of the energy resides in sensor node. The energy consumption of the sensor node in the previous routing protocols does not optimal solutions which leads to a decrease in the lifetime of the WSN.

In the hierarchical approach of WSN, the sensor-nodes are grouped into the form of multiple clusters, where the grouped-nodes as cluster is operated and managed by a single sensor node, known as cluster head (CH) Before the clustering approach, every sensor node sends its data directly to BS, as there is no CH concept. The direct transmission was very expensive in terms of energy consumption due to long-distance and redundant data [2]. To avoid direct transmission, a clustering methodology was introduced in which the sensor nodes select CH within the cluster and update it by sending data to CH. The CH receives the data, removes redundancy from the data, aggregates it, and then sends it to the BS. This whole procedure implies that the CH selection plays a main entity in optimizing the energy consumption of WSN. For the optimal selection of CH, various approaches have been proposed by the researcher. The traditional approaches for optimal cluster head selection are LEACH (Low-Energy-Adaptive-Cluster-Hierarchy) HEED (Hybrid-Energy-Efficient-Distributed), PEGASIS (Power-Efficient-Gathering-in-Sensor-Information-Systems) [3-5], however, recent researches have proved that these techniques have failed to select the "$optimal$" CH particularly with complex optimization functions in WSN. Over recent years, researchers have focused on metaheuristic optimization algorithms as a prospective technique that may offer much improved solutions specifically for the optimal selections of CH in WSN [$6-11$].

In this manuscript, a improved form of PSO is proposed, named *"(MSPSO) Multiple solutions based Particle swarm optimization"*. The algorithm generates optimal solutions by minimizing the number of calling times of the CH selection process as an objective function. For this purpose, the algorithm selects the three best sensor nodes named as $alpha$, $beta$, and $delta$ in each round, which will be selected as CH for the next three rounds without calling the proposed CH selection algorithm. In this way, the decrease of the number of calls for the CH selection algorithm causes the reduction of energy depletion in sensor-nodes, which in turn leads to prolonging the lifetime of the WSN.

This work is structured in the following way: the state of arts Literature review is presented in Section-II, research methodology is given in Section-III. The recommended approach is briefly described in Section-IV and the results are discussed in Section-V. The results are concluded in the

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conclusion-section of the paper as given in Section-VI

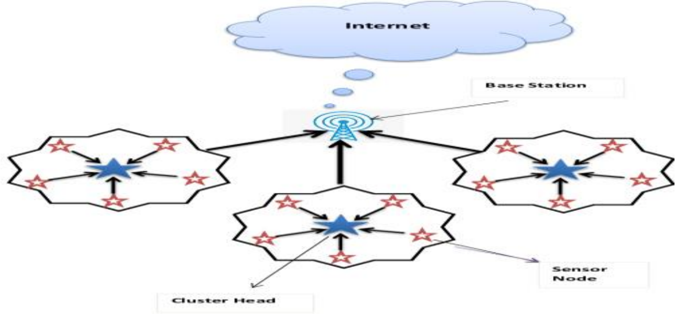

Fig.1 Clustering Based WSN.

II. Literature Review

The efficient utilization of energy-consumption of the sensor-nodes in the wireless-sensor-network is considered as the main issue that seriously damages the network performance. The optimal selection of CH is based on multiple complex objective functions, which make this CH selection a non-polynomial (NP)-hard optimization problem. Many researchers have proposed a diverse approach to resolve this problem but still, there is a gap for improvement. For such kinds of optimization problems, the heuristic approaches like LEACH, HEED, and PEGASIS are applied in the past but these approaches are not considered favorable techniques for NP-Hard optimization problems. Nevertheless, meta-heuristics have gained momentous popularity in the area of NP-Hard optimization problems, as they offer much improved solutions compared to heuristic techniques [12]. Peng [3] present a LEACH as the most popular protocol for clustering algorithm, in which the sensor node is elected based on likelihood or probability. LEACH reduces energy depletion and prolongs the lifetime of the WSN. The main issue in LEACH is that it selects CH randomly. There is a possibility that it chooses the sensor node with low energy which can die soon after selection. The work presented in [4] proposed a HEED approach in which the CH is nominated periodically on the basis of residual-energy and degree of the sensor-node. Lindesy [5] offers an approach called PEGASIS, where the nodes are arranged in a chain, and every node receives and sends data to its neighbor. The problem in PEGASIS is that when the size of network is increased; its energy-usage will also be increased. Wang [13] proposed a PSO as a CH selection technique while considering the residual energy and its position. Sarkar [14] presents a firefly algorithm for the optimization of CH-selection. In this approach, the distance between CH and BS, and intra-cluster-distance is considered as the objective function for the selection of CH. Due to nearest to BS and other sensor nodes the transmission delay is minimized which leads to reduce the energy-utilization and increase lifetime of WSN. The drawback of this method is the probability of sensor-node selection having decreased residual-energy and will die rapidly. A hybrid model of LEACH and Monkey-Search has been proposed by Shankar [15]. For the CH selection, the author offered a hybrid model of LEACH and Monkey-Search-algorithm for better utilization of network-energy, increase throughput, and maximize the lifetime of the WSN. The selection of CH is based on the distance between BS and CH intra-cluster distance and residual energy of the sensor node. Reddy and Jadhvi $[7-8]$ proposed WOA for the selection of CH. the authors considered residual energy and intra-cluster distance but did not consider the distance between CH and BS. Garg [9] offered the CH selection technique by evaluating the distance between CH and BS and remaining energy-intra-cluster-distance. His results show improvement in the growth in quantity of live sensor-nodes and lifetime of the WSN. Latiff in [11] proposed the PSO clustering technique by optimizing the distance among sensor nodes within the cluster and remaining energy. The authors did not consider the distance between BS and CH. Lalwani [16] presents a new algorithm named optic inspired optimization algorithm for clustering and optimizing the routing-path its fitness function tries to optimize the remaining sensor-node's energy, degree of sensor-node, and the distance. The proposed approach three sensor-nodes will be nominated or selected on the basis of ranking terminology to their fitness values which will have the following benefits:

- Reduce the calling of the CH selection algorithm to one-third.
- Optimize the energy consumption in CH selection.

III. Research Design and Methods

In this section, a model is presented for the optimization of energy consumption in WSN.

A. Energy model

When the sensor node transmits a radio signal it will consume network`s energy, and it is directly proportional to the amount of data and the space or distance at which the data is to be transmitted. The total energy required for the sensor node to transmit its data is given by:

$$E_{\mathrm{T}}(N:r) = \begin{cases} E_c * N + E_f * N * r^2 & If\ r < r_0 \quad (1) \\ E_c * N + E_m * N * r^4 & If\ r \geq r_0 \quad (2) \end{cases}$$

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{3}$$

Where E_c is the energy consumption by electronic circuitry, E_f is the energy consumption when it transmits through free space, N is the amount of the information-bits that are to be spread. r is the distance between CH and BS. When r is less than r_0 then the total energy consume E_T will be calculated through Eq. (1) otherwise E_T will be calculated through $Eq.(2)$. If node receive n bit then the energy consumption of the node will be

$$E_{\mathrm{R}}(N) = N * E_{\mathrm{c}} \tag{4}$$

During the idle and sensing status, the energy consumption is denoted by E_i and E_{s}, respectively. The total energy of the sensor node is given by;

$$E_{Tot} = E_{\mathrm{T}} + E_{\mathrm{R}} + E_i + E_{\mathrm{s}} \tag{5}$$

B. Distance measurement

The distance between BS and CH is to be calculated as;

$$D(ch, BS) = \sqrt{(ch_y - BS_y)^2 + (ch_x - BS_x)^2} \tag{6}$$

C. Fitness Function

Through fitness function, all nodes are evaluated, based on the fitness values the selection of CH is performed. The fitness-function of the projected approach is dependent on three entities, which are residual-energy, the distance between CH and BS, and intra-cluster-distance.

1. Intra-Cluster-Distance

To minimize the sum of the distance between a node and CH, which should be minimized, the following function can be used;

$$minimize\ Dist_{intra} = \sum_{i=1}^{n}\sum_{j=1}^{n}\sqrt{\frac{\|pi - pj\|}{2}} \tag{8}$$

Where p_i, and p, are the position of nodes within the cluster, and $i = 1 \ldots n$ is the amount of sensor-nodes in a cluster.

2. Distance between CH and BS

To calculate the distance between CH and BS, which should be minimized, the function is given as;

$$min\ Dist_{CH-BS} = \sum_{i=1}^{n}|pi - BS| \tag{9}$$

Where pi is the position of CH.

3. Residual-Energy within CH

The sensor-node which has high residual-energy will have the high priority to be selected as CH. For calculating the function is used;

$$Maximize\ E_{res} = \sum_{j=1}^{n} E_{ch_i} \tag{10}$$

Where

E_{ch_i}=E-{ $E_{x_i,\rightarrow ch}$ *k +$E_{ch\rightarrow x_i}$ *h +D_{BS-CH} *p + $E_{sens+idle}$ *q}

While $0 < E < threshold$

where k represent the amount of bits, which have to be communicated from the sensor node to CH, h represents the number of bits to send from the CH to the sensor node and q is the number of a time slice for which sensor node is live.

The *MSPSO* will minimize the linear combination of three parameters in a single objective function which is given as;

$$Min\ Fitn = (\alpha * Dist_{CH-BS} + \beta * Dist_{intra^2}) + \frac{\Omega}{E_{res}} \tag{11}$$

IV. PROPOSED ALGORITHM FOR CLUSTER HEAD SELECTION

Within each cluster, CH plays an important role as it collects the data from the further sensor-nodes, performs the different aggregate operations on them, and then sends it to the BS. The energy of the CH is decreasing rapidly compared to other nodes as it has the extra burden of receiving data for other nodes of the cluster, processing that data, and send it to the BS. Therefore, the optimal selection of CH in the cluster is needed to be decreased the energy-utilization of the sensor-node. In the proposed technique *MSPSO* three best sensor nodes based on their optimal fitness values, name $alpha, beta,$ and $delta$ are selected for the CH in each round. $Alpha, beta,$ and $delta$ are stored in BS and then BS announces alpha primary choice as CH of the cluster. When the energy of $alpha$ is decreased from the pre-defined threshold level, it will handovers the charge of CH to BS and the BS declare $beta$ as CH. when the energy of $beta$ is decreased from the threshold level, it handover the charge of CH to BS and BS state $delta$ as CH without calling the CH selection algorithm. This methodology causes the saving of the calling of CH selection algorithm repetitive process, and thus the energy usually consumed in the calling algorithm process is saved. When the BS calls the algorithm it must have to collect the information such as residual-energy from sensor-node. By sending along with computing the residual-energy the sensor-node is consuming energy which will be reduced. In this manner, the energy-depletion is reduced and lifespan of the overall WSN-network will be improved. The proposed algorithm of *MPSO* is demonstrated by means of pseudocode, as shown in *Algorithm-I*.

ALGORITHM-I. PSEUDOCODE OF PROPOSED ALGORITHM

(1) set *MPSO* population X_i $(i = 1, 2, \ldots, n)$
(2) Evaluate the fitness-value for each searching-agent
(3) Find X_α=searching-agent having optimal value
(4) Find X_β= searching-agent having 2^{nd} ranked value
(5) Find X_δ= searching-agent having 3^{rd} ranked value
(6) ***While***(*it<maxit*)
(7) ***For***
(8) Update the velocity of the agents
(9) Update the position of the agent
(10) ***for end***
(11) Update $X_\alpha, X_\beta, X_\Omega$ if a better solution is available.
(12) *it=it+1*
(13) ***While end***
(14) ***Return*** $X_\alpha, X_\beta, X_\Omega$

V. RESULTS AND DISCUSSION

The simulations of the *MSPSO* algorithm for CH selection are conducted in MATLAB $R2018a$. The methodology of the proposed CH selection algorithm considered the abovementioned objective functions $i, e.$ intra-cluster-distance, the space/ distance between the BS and sensor-node, and the space of the remaining nodes. All the sensor node is considered to be static and homogeneous type. The experimental setup is dependent on numerous factors, which are given in Table I.

A. Residual Energy Based Performance Comparison

$Fig.2$ displays the total-residual-energy of the sensor-nodes by utilizing the approaches of MSPSO, PSO, WOA, Bat, and GWO during several iterations. It can be observed from $Fig.2$ that the sum of all node's residual energy at each iteration in *MSPSO* is higher compared to PSO [19], GWO [17], WOA [20], and Bat [18, 21 – 22]. This implies that the WSN will maintain a higher amount of residual energy by using the *MSPSO* approach.

B. *Live nodes Based Performance Comparison*

$Fig.3$ depicts the number of live nodes in each iteration by utilization the algorithms of *MSPSO*, PSO, WOA, Bat, and GWO. It can be being observed from the result that MSPSO offers a maximum sum of Live-nodes for longer amount of rounds. This implies the rate of energy consumption in *MSPSO* is lower than PSO, WOA, Bat, and GWO, which in turn increase the active sensor node's overall lifespan of WSN.

C. *Convergence to the optimal value Based performance comparison*

In $Fig.4$, the convergence rate for each abovementioned algorithm is compared for finding the optimal solutions concerning given objective functions of WSN application. From $Fig.4$, it is witnessed that the convergence-rate of *MSPSO* is far better compare to PSO, WOA, Bat, and GWO for the optimization of WSN.

VI. CONCLUSION

This paper offered the $MSPSO\ CH$ selection technique which provided the optimal solutions in the form of effective CH selection within the clusters of WSN. For optimization of WSN, three objective functions were considered as the remaining-energy of the sensor-node, CH to BS distance, and distance among the sensor-nodes in the cluster. During the experimental process, the results were measured with respect to several live nodes, total energy residual consumption, and convergence rate. For the conducted experiments, the proposed *MSPSO* is compared with other well-known metaheuristic approaches, where were previously used for the given optimization. The simulated outcomes prove that the offered *MSPSO* approach is successful in increasing the number of live nodes, fast convergence rate, and increase the average residual energy of WSN compared to GA, PSO, and WOA.

TABLE I. WIRELESS SENSOR NETWORK PARAMETERS

Parameter	Value
Target area	100-by-100 m^2
Base station location	(250,200)
The initial energy of the node	20j
Threshold when CH leave it to service as CH	50%
Number of sensor node	200

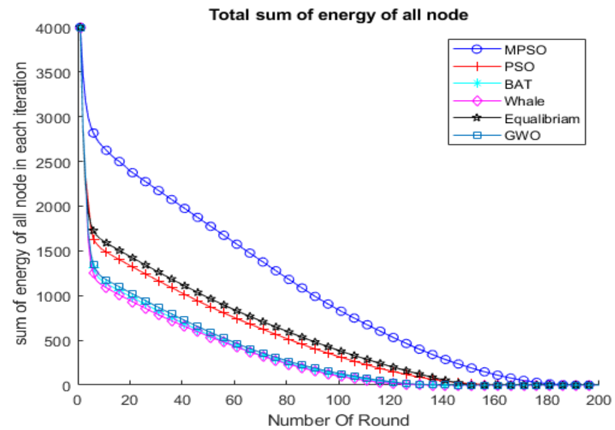

Fig. 2. *Residual Energy Based Performance Comparison*

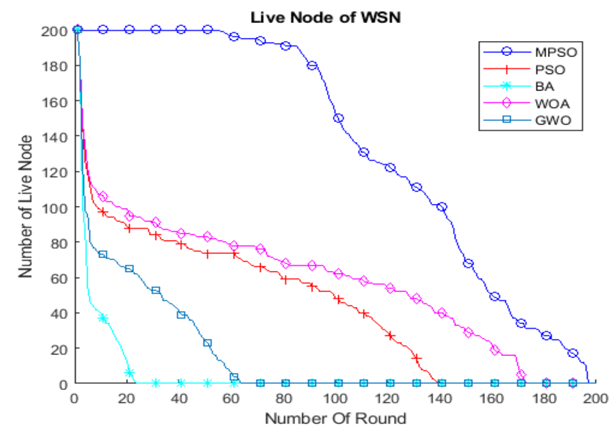

Fig. 3. Live nodes Based Performance Comparison

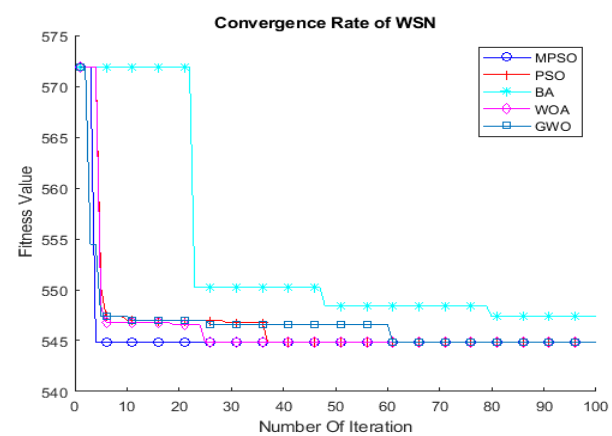

Fig. 4 *Convergence to the optimal value Based performance comparison*

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