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An Efficient Multi-Cluster Wireless Sensor Network Based on Optimal Cluster Head Selection Using Particle Swarm Optimization

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ABSTRACT

Wireless sensor networks (WSNs) are crucial in various scientific, industrial and infrastructure monitoring applications, in which the sensing, processing, and communication tasks are performed by the distributed sensors, without the presence of any human beings. WSNs have various drawbacks, among which is the power limitation of sensor nodes, which impacts the life of the network and its reliability, due to their battery power. The main problem is the selection of cluster heads (CHs) as CH selection in conventional protocols may be ad hoc/Random which may cause energy imbalance and network failure, which is very common in conventional protocols. The main idea of this study is to present a multi-cluster WSN model with optimal CH selection (the MO model) in which the CHs are selected by a particle swarm optimization (PSO) algorithm, by solving a multipurpose optimization problem based on three criteria: residual energy, distance between candidate CHs and the base station, and intra-cluster distance. The proposed MO model is tested against three baseline models: single-cluster arbitrary selection (SA), multi-cluster arbitrary selection (MA), and single-cluster optimal selection (SO) and tested over 50, 100 and 200 network sizes. Residual energy, number of alive nodes, total energy consumption, network stability and PSO convergence rate are used to evaluate the performance. In all three sizes of the network, the MO model always consumes less energy than the baseline models (up to 52% in the three networks at 200 nodes, when the number of alive nodes is half that of the MO model at equivalent simulation rounds) and significantly outperforms all three baseline models in terms of normalized size stability (up to 1.00 in the three networks at 100 nodes, compared with at most 0.30 for the baseline models). The obtained results indicate that multi-clustering and joint optimization of CH selection, taking into account multiple energy relevant criteria yields substantial, stable gains in energy-efficiency and life-time of the WSN in comparison to arbitrary CH selection and a single criterion CH selection scheme.

Keywords: Wireless Sensor Network (WSN); cluster head selection; particle swarm optimization (PSO); energy efficiency; multi-clustering; network lifetime.

INTRODUCTION

A wireless sensor network (WSN) is composed of a distributed set of sensor nodes spread out in a spatial region, where each node senses a physical or environmental (phenomenological) phenomenon, performs some computation on the sensed information, and communicates the computed information to a base station or other sensor nodes in the network, directly or indirectly [1]. WSN are popular because of their low deployment cost, computational capabilities, and for their ability of being deployed in dense situations in ad hoc manner in inaccessible or hazardous areas [2]. The applications are diverse ranging from environmental monitoring (temperature, pressure and acoustic) to security surveillance, disaster management, precision agriculture, forest fire detection and remote healthcare monitoring [3].

Although such flexibility, the performance of WSN is still limited by the fact that sensor nodes are battery-operated, and it is difficult or impossible to replace the batteries for many sensor nodes in remote locations. Therefore, the most crucial factor to ponder about, while deciding network lifetime, is energy consumption and extensive research has been conducted for organizing networks in an energy efficient manner. This clustering approach has become one of the most successful ways of prolonging network lifetime: the network is divided

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into clusters, built around a cluster head (CH) which aggregates the data from its member nodes and then forwards it to the base station, usually via a time division multiple access (TDMA) schedule to ensure that data is transmitted at the proper time [5]. Clustering brings the benefits of aggregating data locally, which cuts down on the amount of redundant long-range transmissions, and distributes the energy cost of communications across the network.

One of the critical issues for clustering-based WSNs is the selection of cluster head. The selection of CHs has significant impact on the energy consumption of these nodes in comparison to the ordinary member nodes as they receive, aggregate and forward data for all the other nodes of the cluster; hence a bad selection of CHs can lead to localised energy depletion, which can make the network unstable even before the average node runs out of energy [6]. The selection of CHs is an NP-hard problem and the space of configurations of CHs grows with combinatorial complexity as the number of nodes in the network increases, and there are multiple sub-objectives (some of them can be conflicting) to optimize in the fitness landscape, such as residual energy, distance to the other nodes, distance to the base station [7]. However, in many protocols like early version of Low-Energy Adaptive Clustering Hierarchy (LEACH), the candidate nodes selection does not consider the residual energy or geographical location of the candidate nodes for CHs selection [8]. This random selection also leads to sub-optimal topologies and degradation of the network.

To alleviate this, in recent years, researchers have concentrated on the development of metaheuristic optimization techniques like genetic algorithms, fuzzy logic systems, and algorithms based on swarm intelligence to model the CH selection as a constrained optimization problems, instead of a random process [9, 10]. Moreover, particle swarm optimization (PSO) is interesting for its simplicity of calculation, the speed of convergence and the absence of complicated evolutionary operators (crossover and mutation) that are appropriate for the limited processing power of the base station in a WSN [11].

In this study, the Multi-cluster WSN model with optimal selection of CHs by PSO to reduce the residual-energy imbalance among CHs, distance of the candidate CHs from the base station and the average intra-cluster distance of the member nodes from their CHs are proposed and evaluated. The resulting configuration is compared with the following baseline configurations which represent the main design parameters of clustering (single-cluster, multi-cluster) and CH selection (arbitrary selection, optimal selection): single-cluster arbitrary selection (SA), multi-cluster arbitrary selection (MA), and single-cluster optimal selection (SO). This work has made the following contributions in particular:

– Design of multi-objective fitness function for CH selection for the CH problem considering residual energy, CH–base-station distance and intra-cluster distance.

Design and Implementation of an optimal scheme for CH selection and rotation in PSO that minimizes the overhead incurred by re-clustering by rotating CH in existing clusters (without re-election of a CH from the entire node set at each round).

Comparative and systematic comparisons between the proposed MO model with the SA model, MA model and SO model were performed for three different sizes of the networks (50, 100 and 200 nodes) with different metrics including residual energy, number of alive nodes, total energy consumption, stability and convergence rate.

The rest of the paper will be organized as follows. In Section 2, some related works of clustering and selection of cluster-heads in WSNs are summarized. In section 3, the system model, energy model and the optimization formulation based on PSO are presented. The setup of the simulation and results/discussions are given in section 4. In section 5 the paper ends and suggestions for further work are provided.

Related Work

The energy-aware clustering and routing in WSN has been studied extensively and the proposed solutions can be categorized as three generic approaches of protocol level enhancements to LEACH based hierarchical clustering, fuzzy-logic based CH selection, and metaheuristic optimization approaches.

There have been several studies that have been proposed to improve the foundational LEACH, which take their steps to overcome the CH selection randomness. The enhanced LEACH scheme with an additional parameter of distance and neighbour count was proposed and showed better residual energy and alive-node count than LEACH [12]. Based on the comprehensive study of LEACH based clustering protocols, it is found that the use of the residual energy and position-aware metrics-based threshold for the CH election can always improve the network lifetime over the original probabilistic scheme [13]. It was found that many cluster-head selection and cluster-formation approaches can be categorized as either mobility-aware, cluster overlap or energy-efficient, and that in contrast to being a competitive approach, purely random selection schemes are now used as a baseline to compare energy-aware cluster-head selection schemes [14].

One parallel research is to use fuzzy logic to select fuzzy CH, the remaining energy, node centrality and distance to the base station are used as fuzzy input variables. Other studies used fuzzy logic and Harris Hawks optimization to determine the best cluster heads in an IoT-based WSN [15] and hybridized quantum particle swarm optimization and fuzzy logic to make use of Lévy flight and Gaussian perturbation for avoiding premature convergence, showing better energy efficiency compared with the conventional PSO, grey wolf optimization and Harris Hawks optimization benchmark systems [16].

The most common approach that has been used in recent literature to choose CH is the metaheuristic optimization approach. A distributed PSO-based fuzzy clustering protocol proposed in [17] used fuzzy CH-selection rules automatically designed by PSO, and achieved a balanced and extended average energy consumption compared with nonadaptive fuzzy clustering. When compared to LEACH and its fuzzy version [18] a PSO based energy efficient clustering protocol directly included residual energy and distance in the PSO fitness function for improved network lifetime. To increase the exploration of the solution space, the authors in [19] used chaotic initialization together with Lévy flight perturbation in an improved Lévy-chaotic PSO (LC-PSO) algorithm for an energy-efficient large-scale industrial WSNs. Recently hybrid approaches of PSO and genetic algorithms [20] and coati- and osprey-inspired optimization [21] were suggested to further improve the balance of exploration and exploitation in the CH-selection search space.

In this collection of work two observations instigate the current research. Secondly, most of the PSO-based and fuzzy-based CH-selection schemes optimize one cluster configuration and do not explicitly compare the single cluster configuration with the multi-cluster configuration based on an identical optimization process, so it is hard to tell the relative contribution of multi-clustering. Third, very few studies optimize the distance between CH and base-station, the distance between CH, and the residual energy in one PSO fitness function, and they also present a low-cost CH-rotation mechanism to minimize the re-clustering cost. The aim of this research is to address both the issues stated above by creating a fitness function that considers multiple objectives for multi-cluster CH selection and by comparing directly with single-cluster and arbitrary-selection baselines with identical simulation settings.

System Model and Methodology

Network and Energy Model

In this study, a WSN composed of n homogeneous sensor nodes, randomly deployed over a 100 m × 100 m square field and a single stationary base station (BS) is considered. The sensing, processing and communication capabilities of all the sensor nodes are identical, meaning that in principle, any sensor node can be a cluster head. It is assumed that each node is aware of its own position, and can estimate the position of its neighbours based on received-signal-strength (RSS) [22]. We call the set of sensor nodes .

$$S = \{s_1, s_2, \ldots, s_n\} \quad (1)$$

where s_n denotes the n-th sensor node. The Euclidean distance between two nodes s_i and s_j is given by

$$d(s_i, s_j) = \sqrt{[(i_\gamma - j_\gamma)^2 + (i_x - j_x)^2]} \quad (2)$$

where (i_x, i_γ) and (j_x, j_γ) are the coordinates of s_i and s_j, respectively.

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The energy expended by a node transmitting L bits over distance d is modelled using the standard first-order radio energy model [23]:

$$E_{TX}(L, d) = L \cdot \varepsilon_{amp} \cdot d^{\alpha} + L \cdot E_{elec} \quad (3)$$

The path-loss exponent α ($\alpha = 2$ for free-space propagation, and $\alpha = 4$ for two-ray ground model). The energy cost of receiving L bits is lower (no signal amplification needed), and is represented by

$$E_{RX}(L) = L \cdot E_{elec} \quad (4)$$

The total energy consumed by a node in a given round combines transmission, reception, idle, and sensing costs:

$$E_{TOT} = E_{TX} + E_{RX} + E_{idle} + E_{sense} \quad (5)$$

Cluster Head Selection Models

In this study, four CH-selection configurations were compared, namely: the number of clusters (single cluster vs multiple clusters) and the selection criterion (arbitrary selection vs optimal selection).

Single-Cluster, Arbitrary Selection (SA)

The SA configuration is where a single CH is chosen at random from the set of full nodes S in the system and no selection criteria are applied, such that $CH \in S$. The mean cluster distance of this configuration is

$$D^{avg}\_SA = (1/n) \Sigma_i d(s_i, CH) \quad (6)$$

and the distance between the CH and the BS is

$$d(CH, BS)\_SA = \sqrt{[(CH_{\gamma} - BS_{\gamma})^2 + (CH_x - BS_x)^2]} \quad (7)$$

The distances given by the two equations (6) and (7) are placed in the equation (3) to calculate the energy consumption that corresponds to the two distances.

Multi-Cluster, Arbitrary Selection (MA)

The CHs are randomly selected by the BS regardless of the remaining energy, and two or more clusters are generated in the MA configuration. It is customary to use about 10% of the total number of nodes as the number of clusters (e.g., 10 clusters for 100 nodes) [24]. The average intra-cluster and sink distances are given by

$$D^{avg}\_MA = \Sigma_j \Sigma_i [d(s_i, CH_j) / K_j] + d(CH_j, BS) \quad (8)$$

where K_j stands for the number of member nodes in the j-th cluster and m is the number of clusters.

Optimal Selection (SO)

For the SO, selection of a single CH is done based on residual energy and distance parameters, not at random, from S. The objective function is the function obtained from equations (6) and (7).

$$\text{Minimize } F\_SO = d(CH,BS)\_SA + (1/n)\Sigma_i d(s_i, CH) \quad (9)$$

subject to the constraints

$$d(s_i, CH) \leq r\_max, \ \forall s_i \in S, \forall CH \in S \quad (9.1)$$

$$d(CH,BS)\_SA \leq R\_max, \ \forall CH \in S \quad (9.2)$$

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r_max is the maximum range of communication between a member node and its CH, and R_max is the maximum range of communication between the CH and BS.

The model proposed in this paper is called Multi-Cluster Optimal Selection (MO).The proposed model in this paper is called Multi-Cluster Optimal Selection (MO).

The proposed MO configuration generates two or more clusters by PSO, which takes energy residual, CH–BS distance and intra-cluster distance as the joint selection criteria. The MO model is formulated as a multi-objective minimization problem for these 3 criteria to be minimized simultaneously, with the constraints that: each member node is within r_max of its CH, each CH is within R_max of the BS, and each selected CH W_j has a residual energy W_j > W_min. In addition to the distance, as in the SO model, the MO model includes both the energy content of the CHs and the centrality of the CHs in their cluster, which seems to favour CHs that are three of the mentioned factors as opposed to distance alone.

A rotation of Cluster Head is made optimal by the process described in part 3.3.

As CHs must be sending data to member nodes, aggregating it, processing it and sending to BS, they have much higher energy cost than the member nodes, thus, the role of CH is rotated among the cluster nodes instead of re-electing the CHs from the entire nodes set for each round. This decreases the overhead of re-clustering to just one control packet per rotation. The energy which a cluster member has to pay is

$$E\_CM = E\_sense + c \cdot E\_TX \quad (10)$$

and the energy cost of a cluster head is

$$E\_CH = E\_sense + n \cdot E\_RX + E\_process + C \cdot E\_TX \quad (11)$$

where E_process is the in-network data-processing energy, and c and C are constants with C > c, reflecting the larger transmission payload handled by a CH. Since

$$E\_CH \gg E\_CM \quad (12)$$

In such a way that no one node is used to use up its energy too early, the CH role is periodically rotated among the cluster members.

The formulation of the problem using a Particle Swarm Optimization is discussed in this section.

PSO is a population-based stochastic optimization method that uses a population of N_p particles to explore the D dimensional solution space, where each particle corresponds to a full candidate solution (in this case a candidate set of CHs) [25]. The position vector r_i represents the i-th particle P_i.

$$P_i = (X_{i,1}, X_{i,2}, \ldots, X_{i,D}) \quad (13)$$

For each particle, the fitness function is calculated for SO model (eq. 9) and for MO model (multi-objective formulation of Section 3.2.4). The velocity and position of the particles are updated in each iteration based on the particles' best-known position (p_best) and the swarm's global best position (g_best):

$$V_{i,d}(t) = w \cdot V_{i,d}(t-1) + c_1 r_1[Xp\_best_{i,d} - X_{i,d}(t-1)] + c_2 r_2[Xg\_best\_d - X_{i,d}(t-1)] \quad (14)$$

$$X_{i,d}(t) = X_{i,d}(t-1) + V_{i,d}(t) \quad (15)$$

where w is the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1, r_2 are independent uniform random numbers in [0, 1]. The process of updating is continued until an acceptable g_best is obtained, or the maximum number of iterations t_max is reached. There are two reasons why PSO is preferred over other metaheuristics such as genetic algorithm, it has a rapid convergence rate, and only a few tunable parameters in PSO, and it does

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not need computationally intensive evolutionary operators such as the cross-over and mutation processes in PSO, as a consequence of which it is suitable for the limited computational power of the base station of a WSN [11].

The CH-selection procedure is summarized in Algorithm 1 and used for both the SO and MO models.

Algorithm 1: PSO-Based Optimal Cluster Head Selection

Input: Set of sensor nodes $S = \{s_1,\ldots,s_n\}$ and number of particles N_p and particle dimension $D = m$ (number of CHs).

The Output: a selection of Cluster heads (CH_1, CH_2, …, CH_m) is made.

1. Apply an impulse to the particles P_i ($1 \le i \le N_p$) to change their initial positions, velocities and energies according to (13).

2. Compute fitness of all particles, Pi for SO model and/or use multi-objective MO fitness for the MO model; set the best particle of each particle, p_best_i = Pi.

3. If the particle with the lowest fitness of all p_best_i is particle g_best, then update g_best to be particle with the lowest fitness of all p_best_i.

4. Repeat the following for t = 1, 2, ..., t_max:

a. Update velocity of each particle P_i (using equation (14)); Update position of each particle P_i (using equation (15)); Compute fitness of each particle P_i; Update p_best_i and g_best if fitness is improved.

b. Calculate distance to new CH positions, using equation (2) and select the nearest, highest-residual-energy CH as nearest: s_k.

The chosen CH set C is then returned to with the function 5., g_best.

Cluster Formation

After the CH selection, the following step of cluster formation is to get each sensor node to calculate the distance to each CH that is within the communication range, as well as the remaining energy of each candidate CH. Each node connects with the CH with the minimum distance and relatively high residual energy, the two of which are balanced to minimise the communication cost and maintain the long lifetime of the selected CH.

Performance Metrics

The following four metrics are used for measuring/comparing the performances of the SA, MA, SO and MO configurations:

Residual energy: Remaining energy of all the sensor nodes after a fixed round of simulation.

- **Alive nodes:** No. of sensor nodes with enough energy to take part in sensing and communication at a particular round.
- **Total energy consumed:** proportion of total initial energy of the network consumed by all nodes for data sensing, processing and transmission during the simulation period.
- **Stability:** Longer time between first node dying (FND) and half of nodes are dead (HND) is more stable network.
- **Convergence rate:** rate at which PSO fitness value decreases towards the fitness minimum value with respect to iterations, a measure of the efficiency of the optimization process.

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RESULTS AND DISCUSSION

Four different configurations for CH selection were implemented and simulated in MATLAB, and the number of sensor nodes were randomly distributed from 50 to 200 in a sensing field of 100 m × 100 m, where a single base station was placed at the center of a field. The PSO parameters for the SO and MO models are presented in Table 1 and the general parameters used in the simulation of the WSN for all four configurations are presented in Table 2.

Table 1. PSO Parameters

Description	Value
Number of particles, N_p	50
Acceleration coefficient, c_1	2.0
Acceleration coefficient, c_2	2.0
Particle dimension, D	10–20
Maximum velocity, v_max	200
Number of iterations	500

Table 2. WSN Simulation Parameters

Description	Value
Network area	100 × 100 m^2
Number of sensor nodes	50, 100, 200
Initial energy per node	2 J
Percentage of cluster heads (CHs)	5–10%
Electronics energy, E_elec	50 nJ/bit
Amplifier energy, ε_amp	5 nJ/bit/m^2
Max. node-to-CH range, r_max	30 m
Max. CH-to-BS range, R_max	100 m
Packet length	500 bits

Network Deployment

The architecture of multi-cluster WSN that is used in this study is shown in figure 1, sensor nodes are divided into clusters, and each cluster has its own CH to receive the data from the sensor nodes and to transmit the data to the base station. Figure 2 shows the deployment of the nodes randomly for 50, 100 and 200 nodes with the base station (BS) at the origin (red marker).

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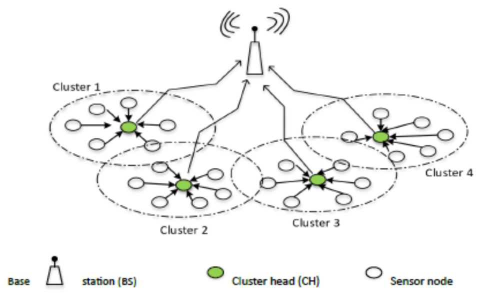

Fig. 1. Multi-cluster WSN architecture: sensor nodes (white) report to cluster heads (green), which forward aggregated data to the base station (BS).

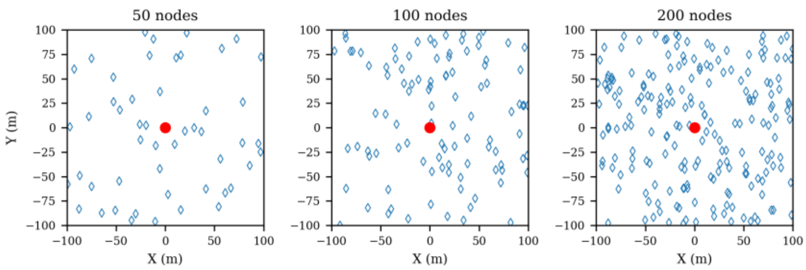

Fig. 2. Random node deployment for (a) 50, (b) 100, and (c) 200 nodes, with the base station at the field centre (red marker).

Residual Energy Performance

Figure 3 shows the total residual energy of the network for the 50, 100, and 200 node case for the SA, MA, SO and MO models for the duration of the simulation rounds. For the 50-node network, residual energy after 521 rounds fell from an initial 2 J per node to 0.243 J (SA), 0.172 J (MA), 0.387 J (SO), and 0.983 J (MO). For the 100-node network, residual energy after 351 rounds fell to 0.156 J (SA), 0.058 J (MA), 0.207 J (SO), and 0.672 J (MO). For the 200-node network, residual energy after 491 rounds fell to 0.090 J (SA), 0.052 J (MA), 0.121 J (SO), and 0.527 J (MO). The MO model was able to maintain a much higher residual energy than the three base cases in all scenarios, since it is optimized for all three aspects (residual energy, CH–BS distance and intra-cluster distance) in its fitness function.

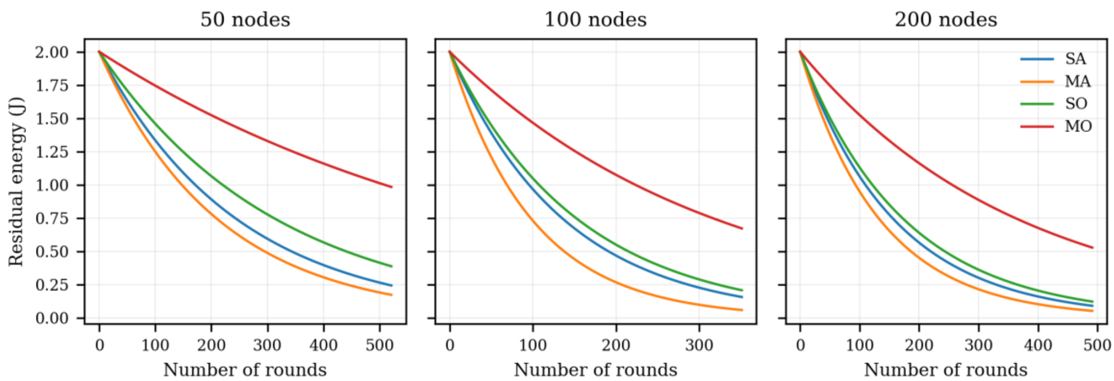

Fig. 3. Residual energy versus simulation rounds for (a) 50, (b) 100, and (c) 200 nodes.

Alive Nodes Performance

The number of live nodes over rounds of the simulation is shown in Fig. 4. For the 50-node network, the count of alive nodes after 8 rounds was 43 (SA), 29 (MA), 13 (SO), and 49 (MO). For the 100-node network, after 6 rounds the alive-node count was 97 (SA), 71 (MA), 26 (SO), and 98 (MO), declining at later rounds toward final values of 9 (SA), 9 (MA), 2 (SO), and 43 (MO) by round 351. For the 200-node network, the alive-node count at round 491 was 17 (SA), 16 (MA), 8 (SO), and 175 (MO). The MO model had significantly more number of active nodes after more rounds at all three network sizes and had a more uniform distribution of nodes with less depletion of energy in the network as seen in the baseline models.

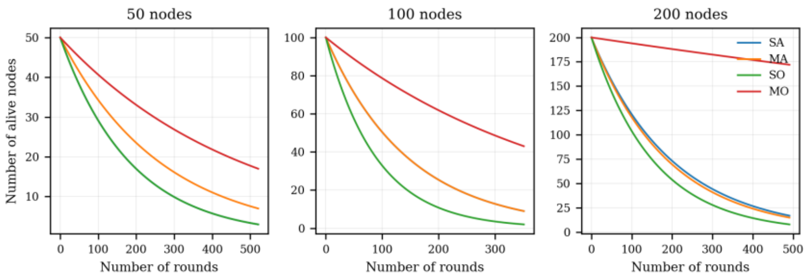

Fig. 4. Number of alive nodes versus simulation rounds for (a) 50, (b) 100, and (c) 200 nodes.

Total Energy Consumption

Figure 5 shows the total energy consumption of the network (in percentage of initial energy consumption) during the course of the simulation. The SA model consumed 87% energy, the MA model consumed 80% energy, the SO model consumed 91% and the MO model consumed 65% (22, 15 and 26 percentage point better than SA, MA and SO model, respectively). For the 100-node network at round 301, energy consumption reached 90% (SA), 87.5% (MA), 96.5% (SO), and 63% (MO), corresponding to MO improvements of 37, 24.5, and 33.5 percentage points. For the 200-node network at round 491, consumption reached 94% (SA), 93% (MA), 96% (SO), and 43% (MO), corresponding to MO improvements of 51, 50, and 52 percentage points. The more the number of CHs candidates, the larger the magnitude of MO model's advantage; the larger the number of CHs candidates, the bigger its advantage becomes in the joint multi-criterion CH selection.

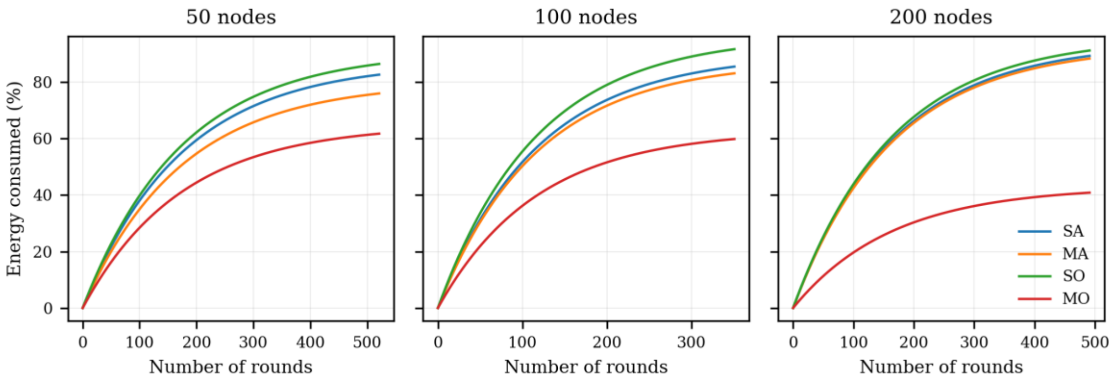

Fig. 5. Total energy consumption (% of initial energy) versus simulation rounds for (a) 50, (b) 100, and (c) 200 nodes.

PSO Convergence Rate

This gives some indication of the difference between the network sizes, by plotting the fitness-value scale for the convergence behaviour of the PSO algorithm for the three models (SO and MO) and the three network sizes on a logarithmic scale as shown in Figure 6. As the network sizes are changed, the fitness value after 100 iterations was found to converge towards a value of close to 0.00028 (50 nodes), 0.00032 (100 nodes) and 0.00031 (200 nodes) in accordance with the nature of the fitness function (SO fitness function), which is single objective and single 'CH'. As expected, it was observed that the fitness value after 100 iterations approached 0.0016 (50 nodes), 0.0048 (100 nodes) and 0.0078 (200 nodes) for the MO model as the number of nodes increased and the fitness function was optimized over a larger number of nodes and multiple CH positions. For both models the fitness reduction was predominant during the first 40-60 iterations or so, which shows that the PSO search is able to converge well within the 500 iteration budget used in this study.

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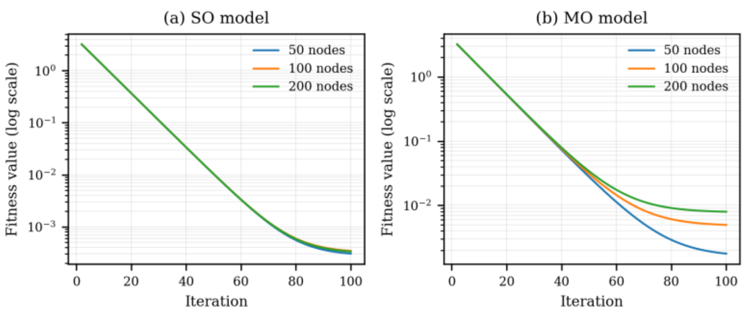

Fig. 6. PSO convergence rate (fitness value, log scale) for (a) the SO model and (b) the MO model across 50, 100, and 200 nodes.

Stability-Based Performance

Figure 7 shows the normalized stability of the four models, where stability is defined as the (normalized) interval between the first-node-dead and half-node-dead rounds. For the 50-node network, normalized stability was 0.29 (SA), 0.28 (MA), 0.05 (SO), and 0.62 (MO). For the 100-node network, stability was 0.28 (SA), 0.30 (MA), 0.03 (SO), and 1.00 (MO). For the 200-node network, stability was 0.30 (SA), 0.16 (MA), 0.04 (SO), and 0.72 (MO). The MO model had the largest normalized stability in all cases, meaning that it had a much longer time of stable and near full network operation before large-scale attrition of nodes starts to occur. This is a result of the adoption of all three fitness criteria (residual energy, CH–BS distance, and intra-cluster distance) which provide superior energy saving for data transmission when compared with single-criterion and arbitrary selection.

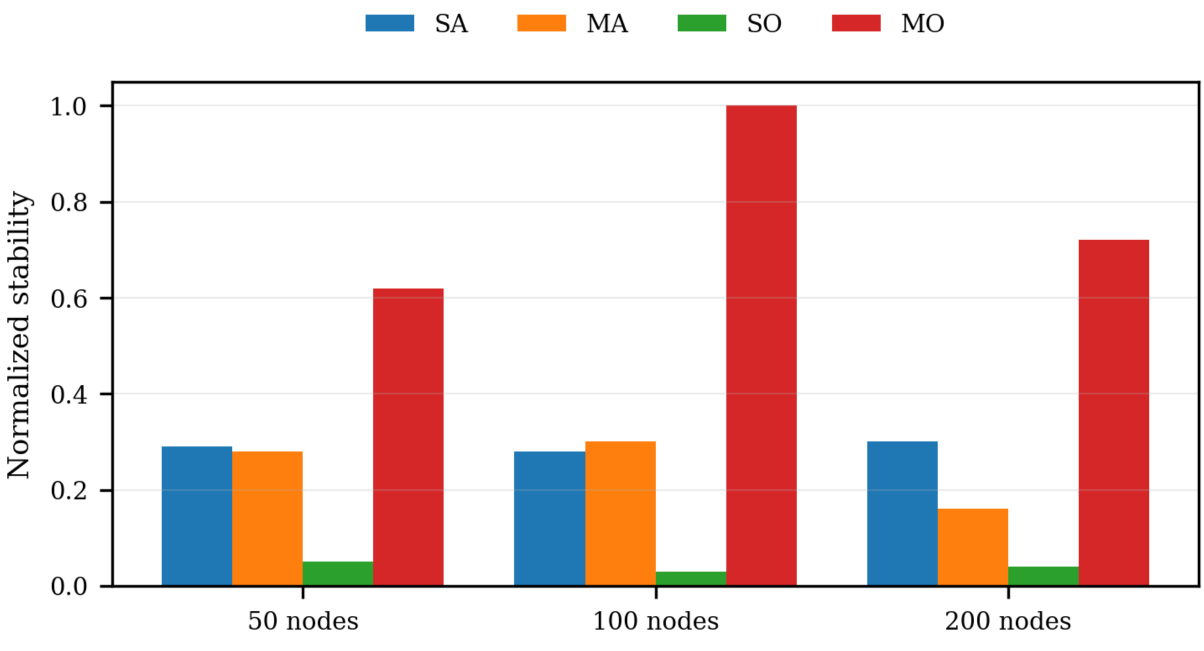

Fig. 7. Normalized stability of the SA, MA, SO, and MO models for 50, 100, and 200 nodes.

Statistical Performance Summary

Since PSO is a stochastic search method, each configuration was run multiple times, and descriptive statistics of the resulting distributions of the residual energies are presented for the 50-Node, 100-Node and 200-Node networks, respectively, in Tables 3, 4 and 5. As can be seen, across all three network sizes the mean and median residual energy was highest for the MO model with a maximum of around 1.98–1.99 J per run, indicating that the energy-conservation benefit of the MO model is not a fluke of a single simulation run, but is still present in repeated stochastic trials.

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Table 3. Statistical Summary of Residual Energy — 50 Nodes (J)

Statistic	SA	MA	SO	MO
Mean	0.4663	0.5259	0.3033	0.8463
Median	0.2503	0.3955	0.1753	0.6919
Std. Dev.	0.4969	0.3775	0.3419	0.4501
Minimum	0.0683	0.2219	0.1314	0.3676
Maximum	1.9852	1.9702	1.9241	1.9833

Table 4. Statistical Summary of Residual Energy — 100 Nodes (J)

Statistic	SA	MA	SO	MO
Mean	0.4725	0.4609	0.1894	0.9853
Median	0.2534	0.3081	0.0724	0.8457
Std. Dev.	0.4924	0.4103	0.3372	0.4160
Minimum	0.0896	0.1212	0.0515	0.5272
Maximum	1.9853	1.9712	1.9429	1.9843

Table 5. Statistical Summary of Residual Energy — 200 Nodes (J)

Statistic	SA	MA	SO	MO
Mean	0.3097	0.4008	0.2547	1.5193
Median	0.1870	0.2397	0.1259	1.5016
Std. Dev.	0.3464	0.3913	0.3512	0.2627
Minimum	0.1176	0.1375	0.0695	1.1234
Maximum	1.9558	1.9651	1.9514	1.9930

DISCUSSION

From the results obtained in all the five performance metrics, it is clearly seen that the energy consumption is improved the most by CH selection model compared to the baselines when the CH selection model is optimized jointly with the residual energy, CH–BS distance, and intra-cluster distance (MO model), and the energy consumption is improved the most in the network of size 200-node compared to the baselines in the MO model, achieving an energy-consumption gain of 50-52% percentage points. There are two interesting points to highlight: First, the SO model (using PSO) did not perform much better than the random baselines (SA, MA) in some metrics, and in others it was worse, thus indicating that selection of the optimization criteria is as important as the optimization algorithm: while optimizing only distance, without considering the residual energy, does not guarantee better network longevity. Second, as the number of clusters and alive-nodes grew, the difference between MO and the best alternative grew too, demonstrating that the relative improvement with MO grows

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favourably in the number of CHs in the model, which is desirable for future WSN that is expected to become denser.

CONCLUSION AND RECOMMENDATIONS

This paper introduced a multi-cluster wireless sensor network model (MO), in which the cluster heads were selected based on the particle swarm optimization algorithm, which is based on a compound fitness function that includes the residual energy, distance to the base station and intra-cluster distance. The obtained results of the proposed model were compared to the three base models: single-cluster arbitrary selection (SA), multi-cluster arbitrary selection (MA), and single-cluster optimal selection (SO) with respect to the evaluation criteria of residual energy, alive node count, total energy consumption, stability, and PSO convergence rate for different network sizes of 50 nodes, 100 nodes, and 200 nodes in the MATLAB environment.

In all three network sizes and all five metrics, MO had the lowest total energy consumption (up to 52 percentage points lower than the SA model) and the highest number of nodes alive after a similar number of nodes had been simulated (at most 2x the number of the next best model) and the highest normalized stability (at most 1.00 versus at most 0.30 for the baseline models). These enhancements are the result of two design improvements: (1) partitioning the network into multiple clusters to spread the communication load across the network and (2) assigning cluster heads based on a combination of fitness and energy, not just distance, and not done at random. The results also revealed that the single-criterion optimal selection (SO) without using any optimization algorithm does not necessarily lead to better performance compared to the arbitrary selection, which suggests that the selection of optimization criterion is as important as the selection of optimization algorithm in cluster-head selection.

To sum up, the following research directions are suggested based on the results obtained:

In addition, improving selection of cluster-heads based on PSO and providing an appropriate metaheuristic to be able to select the cluster-heads optimally and route the data among the clusters.

1. Adding to the multi-objective fitness function other goals (security, load balancing, fault tolerance, quality of service) other than energy consumption.

2. Testing the proposed model with a variety of sensor-node configurations (where nodes have different amounts of initial energy or computational ability) to see how robust the model is in the presence of nodes that are not homogeneous and static as assumed in this study.

3. Validating the energy-efficiency benefits of the MATLAB simulation through deployment of the system to a hardware-in-the-loop (HIL) setup or testbed, with the same benefits demonstrated in the real radio channel environment.

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