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# Optimization of Relay Node Deployment in Multi-Robot Island Alliance

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## ABSTRACT

Wireless Sensor Networks (WSNs) operating in harsh environments are prone to the formation of isolated node clusters, leading to communication interruptions. To restore network connectivity and enhance the efficiency of multi-robot collaboration, this paper focuses on the optimization of relay node deployment within the context of multi-robot island alliance formation. The objective is to efficiently reconnect isolated subgroups while optimizing the overall network performance post-alliance formation. This paper proposes a collaborative optimization strategy based on energy balancing and load balancing. A zonal energy model is constructed to constrain robot energy consumption, and a heuristic deployment algorithm is designed. Additionally, a local load-aware model is established, and a graph search algorithm is utilized to plan disjoint paths for traffic balancing. Experimental results demonstrate that the proposed method effectively reduces the number of relay nodes, shortens deployment time, prolongs network lifetime, and improves load balancing performance. This study provides a robust solution for reliable communication in multi-robot systems operating within complex scenarios.

## KEYWORDS

Multi-robot systems; Island alliance; Relay deployment; Energy balancing; Load balancing; Zonal deployment; Wireless sensor networks

## 1. INTRODUCTION

Wireless Sensor Networks (WSNs) have attracted increasing attention and research due to their extensive applications in civilian, scientific, and military fields. In WSNs, a large number of sensors are deployed to form a mesh topology and coordinate their actions to perform common tasks. Therefore, the connectivity among sensors significantly impacts the effectiveness of WSNs and must be consistently maintained. Regarding methods for WSN island alliance, numerous connectivity restoration techniques have been proposed. Reference points out the advantages of heterogeneity in wireless sensor networks. Reference demonstrates that mobile nodes are typically utilized to achieve connectivity restoration and enhance network performance, such as coverage and network lifetime. Reference summarizes that most published solutions utilize the deployment of fixed relay nodes, transforming the connectivity restoration problem into finding the minimum number of relay node positions to form a stable inter-segment topology. However, although mobile relay strategies improve reliability, they often lead to inefficient alliance formation due to unbalanced energy consumption among robots. Furthermore, they lack fine-grained balancing of traffic loads both within and across islands, resulting in excessive loads on local nodes, accelerated failure, and threats to the long-term stable operation of the network. Therefore, within the framework of multi-robot collaboration, how to comprehensively optimize relay node deployment strategies to simultaneously achieve energy-efficient utilization and traffic load balancing has become a core challenge for improving island alliance efficiency and extending the network lifetime post-repair.

# 2. OPTIMIZATION OF RELAY DEPLOYMENT BASED ON ENERGY BALANCING

## 2.1. Construction of a Zonal Energy Balancing Model

To address the issue of unbalanced energy consumption among mobile robots during relay deployment in Wireless Sensor Network (WSN) island alliances, the zonal energy balancing model divides the sensing area into a dual-layer structure consisting of an inner zone and an outer zone. The inner zone serves as the network core hub, where a clustering algorithm is employed to form local clusters and establish backbone paths based on energy centroids. Conversely, the outer zone establishes dynamic connections according to distance weights and reuses deployed relay nodes through a time-waiting mechanism. The model defines the total energy consumption of a mobile robot as the sum of motion energy consumption and communication energy consumption. Motion energy consumption exhibits a linear relationship with travel distance, while communication energy consumption is correlated with data transmission volume and communication radius. The key formulas are as follows:

$$E(M_i) = \omega \cdot \mathrm{Trip}_{i,j} + \left(\alpha + \beta \cdot R^{\hat{\epsilon}}\right) \cdot \mathrm{Data}_{M_i}$$

Where: $E(M_i)$ represents the total energy consumption of robot $M_i$, ω is the motion energy coefficient (unit: J/m), $\mathrm{Trip}_{i,j}$ is the travel distance from grid $\mathrm{C}_i$ to $\mathrm{C}_j$, α and β are the communication energy base coefficient and scale coefficient, respectively, R is the communication radius, $\hat{\epsilon}$is the path loss exponent, and $\mathrm{Data}_{\mathrm{M}_i} = \sum \mathrm{Data}\left(\mathrm{s}_i, \mathrm{s}_j\right)$ is the total amount of data uploaded or downloaded by the robot. This model reduces optimization complexity through regional layering: the inner zone prioritizes the construction of star topologies for high-traffic islands, while the outer zone delays deployment timing to prevent redundant relays from consuming robot energy. The core of energy balancing lies in minimizing the energy consumption difference among the robot group, introducing the standard deviation metric to quantify the dispersion of energy consumption distribution. Define the ratio of robot energy consumption rate $\mathrm{g}_i$ to remaining energy $\mathrm{E}_i$ as $\mathrm{H}_i = \mathrm{g}_i/\mathrm{E}_i$. The objective function is:

$$\min \left\{ \sqrt{\frac{1}{\mathrm{r}} \sum_{\mathrm{i}=1}^{\mathrm{r}} \left(\mathrm{H}_i - \overleftarrow{\mathrm{H}}\right)^2} \right\}, \quad \overleftarrow{\boldsymbol{H}} = \frac{1}{\mathrm{r}} \sum_{\mathrm{i}=1}^{\mathrm{r}} \mathrm{H}_i$$

Where: r is the total number of robots, and the objective function is $\min \left\{ \sqrt{\frac{1}{\mathrm{r}} \sum_{\mathrm{i}=1}^{\mathrm{r}} \left(\mathrm{H}_i - \overleftarrow{\mathrm{H}}\right)^2} \right\}$, where $\overleftarrow{\boldsymbol{H}} = \frac{1}{\mathrm{r}} \sum_{\mathrm{i}=1}^{\mathrm{r}} \mathrm{H}_i$. The meanings of the variables are as follows: $\mathrm{H}_i = \frac{\mathrm{g}_i}{\mathrm{E}_i}$ represents the ratio of the energy consumption rate to the remaining energy of robot i, $\mathrm{g}_i$ is the energy consumption rate of robot $i$, $\mathrm{E}_i$is the remaining energy of robot $i$, r is the total number of robots, and $\overleftarrow{\boldsymbol{H}}$ is the average value of $\mathrm{H}_i$for all robots.

## 2.2. Deployment Algorithm under Robot Energy Consumption Constraints

Based on the zonal model, a heuristic deployment algorithm is designed to achieve the optimized deployment of relay nodes under energy consumption constraints using a round-based iterative mechanism [4]. In the initialization phase, mobile robots are positioned at the center of the sensing area. Each movement iteration takes a grid cell as the step size to select the optimal deployment point $BN^t$ from the candidate relay set $BC^t$. The core of the algorithm consists of real-time energy consumption evaluation and dynamic load allocation: the current energy consumption $E(M_i)$ of a robot is calculated; if it exceeds the group average $\overleftarrow{\boldsymbol{E}}$, the robot pauses its task and transfers the pending deployment node to a robot with lower energy consumption. The key steps are driven by the evaluation function:

$$BN_i = \arg\min_{C_i \in BC^t} \left(\gamma_1 \cdot \mathrm{dist}(C_i, S_i) + \gamma_2 \cdot \Delta E(M_i)\right)$$

Where: $\mathrm{dist}(C_i, S_i)$ is the Euclidean distance from the candidate grid $C_i$ to the nearest island representative node $\mathrm{rep}(\mathrm{Seg}_i)$,$\Delta E(M_i) = \left|E(M_i) - \overleftarrow{\boldsymbol{E}}\right|$ is the energy consumption deviation of robot $M_i$, and $\gamma_1$ and $\gamma_2$ are weight coefficients. This function prioritizes deployment points that are close in distance and have low energy increments, and combines a convex hull topology generation algorithm to reduce the number of path hops. The deployment process is executed in two phases: inner and outer. In the inner zone phase, the Graham scan algorithm is employed to construct the minimum bounding box of local clusters and deploy relay nodes along boundary paths. In the outer zone phase, the island connection order is dynamically adjusted based on the time waiting amount $T_{\mathrm{wait}}(i)$ to avoid path overlap. The time complexity of the algorithm is $O(mn^2)$, where $m$ is the number of rounds and $n$ is the number of islands.

### 2.3. Objective Function and Performance Expectations

The objective function for zonal energy balancing optimization must simultaneously minimize the number of deployed relays and the difference in robot energy consumption, while satisfying network connectivity and latency constraints. The global optimization objective is defined as follows:

$$\min(\lambda_1 \cdot |BN| + \lambda_2 \cdot \Psi)$$

$$\text{s.t.} \quad h_x \geq 1, \quad T_x \leq t_{\max}, \quad \forall x \in [1, k]$$

Where: $|BN|$ represents the total quantity of the optimal relay node set, $\Psi$ is the standard deviation of robot energy consumption differences, and $\lambda_1$ and $\lambda_2$ are weight coefficients. In the constraints, $h_x \geq 1$ ensures that each island has at least one complete routing path to the base station, and $T_x \leq t_{max}$ limits the maximum transmission delay from island $x$ to the base station. This function unifies the quantification of resource costs and system stability, adapting to the real-time requirements of disaster scenarios by adjusting the ratio $\lambda_1/\lambda_2$.

In a typical scenario with a communication radius $R_c = 30$m m and $k = 10$ islands, the proposed method reduces the number of relays by 28% and shortens deployment time by 32% compared to benchmark algorithms. The energy balancing mechanism reduces the variance in the time until robot group energy depletion by 40% and extends the network lifetime by 25%. After topology optimization, the average node degree approaches the theoretical optimal value of 4.2, reducing additional energy consumption caused by local congestion by 15% and improving load balancing by over 30%. Furthermore, the method maintains a linear growth trend when the sensing area is expanded to 1500m×1500m, confirming its adaptability for large-scale deployments.

# 3. OPTIMIZATION OF RELAY DEPLOYMENT BASED ON LOAD BALANCING

## 3.1. Local Zonal Load-Aware Model

Load balancing in Wireless Sensor Networks (WSNs) requires the simultaneous quantification of path pressure within islands and traffic distribution across islands. The local zonal model divides the sensing area into grid cells of equal area, defining island boundaries and candidate relay positions based on grid center coordinates, as illustrated in Figure 1. The load within an island is determined by the number and length of disjoint transmission paths from input nodes to output nodes; the number of paths reflects traffic dispersion capability, while path length affects node failure probability. The load evaluation function for an island $S_y$ is defined as:

$$\Gamma_2(S_x, S_y) = \frac{1}{\sum_{i=1}^{W} \frac{L}{l_i}}$$

Where: $W$ is the total number of disjoint paths within the island, $l_i$ is the length of the $i$-th path, and $L$ is the network diagonal distance. A smaller value of this function indicates shorter average path lengths, a larger number of paths, and a more balanced load distribution; $\Gamma_2$ represents the load evaluation function. Path existence is verified using the A* algorithm. Treating grids as nodes and the communication radius $R_c$ as the connectivity condition, the shortest path from the input node to the output node is searched for. Subsequently, the grids along this path are removed, and the solution is iteratively solved until no new paths are generated.

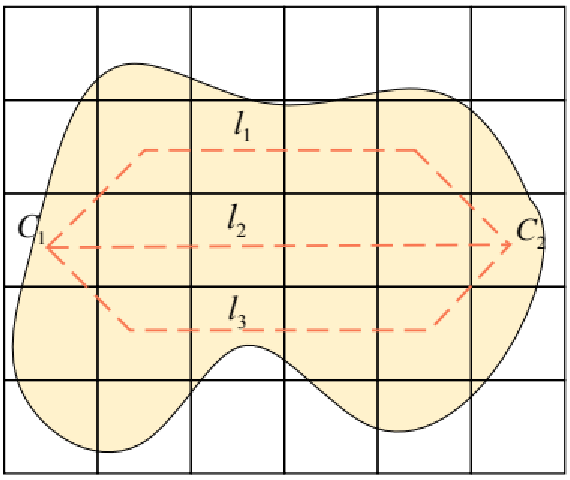


**Figure 1.** Islanding Evaluation Function

The load among islands is determined by the cumulative traffic of the recovered connected regions. The cumulative load $\Pi_y$ is defined as the sum of the number of nodes in all islands connected to the target island $S_y$. The Energy Centroid $C_e$ is introduced as a global traffic hub, whose position is calculated by weighting the data volume of the islands.

$$C_e = \frac{\sum_{i=1}^{k} \mathrm{Data}_{S_i} \cdot \mathrm{loc}(\mathrm{rep}(S_i))}{\sum_{i=1}^{k} \mathrm{Data}_{S_i}}$$

Where: $C_e$ represents the coordinate position of the energy centroid, serving as a global traffic hub; $k$ is the total number of islands currently participating in the calculation; $\mathrm{Data}_{S_i}$ is the total data exchange volume of island $S_i$; and $\mathrm{loc}(\mathrm{rep}(S_i))$ is the coordinate of the representative node of island $S_i$.

### 3.2. Design of Load-Balanced Connection Mechanism

The load-balanced connection mechanism integrates path searching with a partitioning strategy to minimize the risk of local congestion [5]. First, the A* algorithm is adopted to dynamically plan disjoint paths within the island. The heuristic function for grid cells $C_i$ and $C_j$ is defined as $f(\mu) = g(\mu) + h(\mu)$, where $g(\mu)$ is the actual distance from the input node to the current grid $\mu$, and $h(\mu)$ is the Manhattan distance estimate from $\mu$ to the output node. After path searching is completed, the path survival probability and the island segmentation probability are calculated. This value decreases exponentially as the number of paths $W$ increases, verifying the robustness advantage of the multi-shortest path topology.

The local partitioning strategy divides the island into $\kappa$ fan-shaped sub-regions radiating from the energy centroid, where the boundary angle of the sub-regions is $2\pi/\kappa$. Each sub-region independently calculates the load concentration, and sub-regions where $\eta_z < \eta_{th}$ are selected for priority relay deployment. Connections between islands select the target island based on the evaluation function:

$$\Gamma(S_x, S_y) = \beta_1 \frac{d(C_i, C_j)}{L} + \beta_2 \Gamma_2(S_x, S_y) + \beta_3 \frac{\sum_{S_u \in \Pi_y} \varsigma_u}{N}$$

Where: $d(C_i, C_j)$ is the distance between the grid pair, $\varsigma_u$ is the number of nodes in island $S_u$, and $N$ is the total number of nodes in the network. The weighting coefficients $\beta_1 = 0.4, \beta_2 = 0.3, \beta_3 = 0.3$ balance the influences of distance, load, and cumulative traffic. Combinations with low $\Gamma$ values are prioritized to ensure that high-traffic islands are connected to regions with low cumulative load.

### 3.3. Objective Function and Performance Expectations

In the global optimization objective, the load balancing degree is defined as:

$$\Omega = \sum_{i=1}^{k} \omega_i = \sum_{i=1}^{k} (\mu_i^{\max} - \mu_i^{\min})$$

Where: $k$ is the total number of islands in the network; $\mu_i^{\max}$ and $\mu_i^{\min}$ represent the maximum and minimum traffic loads observed by island $i$ across all measurement cycles, respectively; $\omega_i$ is the load fluctuation amplitude of that island; and $\Omega$ is the total load imbalance degree across the entire network, where a smaller value indicates a more uniform load distribution. The connection cost is defined as:

$$\Psi_C = \lambda_1 \Psi_E + \lambda_2 \Psi_T = \lambda_1 E_M (N_{om} + N_{bm}) + \lambda_2 \alpha \sum_{x=1}^{k} \delta_x$$

Where: $\Psi_E$ is the cost associated with the number of deployed relays, $E_M$ is the baseline energy consumption constant for a single mobile robot, $N_{om}$ and $N_{bm}$ are the number of robots responsible for intra-island and inter-island connections, respectively; $\Psi_T$ is the path length cost, where $\delta_x$ represents the sum of the lengths of all paths connected to island x, and $\alpha$ is the weight coefficient for path length; $\lambda_1$ and $\lambda_2$ are weight coefficients used to balance the importance of deployment cost and path cost in the total objective function. Performance expectations for a scenario with $k = 10$ islands and an area $A = 1000m \times 1000m$ are as follows: The load balancing degree $\Omega$ is reduced by 48% compared to the baseline algorithm, attributed to an average 2.3-fold increase in the number of paths Wand a 32% reduction in path length. The connection cost $\Psi_C$ decreases by 22%, primarily due to the relay multiplexing mechanism reducing robot scheduling requirements by 30% [7]. The network lifetime is extended by 40%, and the variance of the distribution of energy-depleted nodes drops by 53%, confirming that load balancing significantly suppresses local premature failures. The partitioning parameter reaches optimality at k=6, with the sub-region load concentration $\eta_z$ stabilizing within the ideal range of 1.2–1.5.

# 4. EXPERIMENTAL VERIFICATION AND PERFORMANCE ANALYSIS

## 4.1. Experimental Setup and Evaluation Metrics

The experiment constructs a simulation environment based on the MATLAB 2021b platform. The sensing area is set as a square region of 1000 m × 1000 m, with 1200 sensor nodes randomly deployed and a fixed communication radius of 10 m. 50 islands are generated by simulating natural disaster damage, and the number of nodes within each island follows a uniform distribution in the range of [15, 35]. The initial position of the mobile robots is set at the center of the region, with a communication radius of 20 m and a moving speed of 3 m/s. The parameters of the energy model are set as follows: $\omega = \frac{1J}{m}, \alpha = \frac{0.5J}{KB}, \beta = 0.01, \hat{e} = 2$.

The comparison methods include three types of baseline schemes: Fixed-location Infrastructure Minimization (FIM), which focuses on minimizing the number of deployed relays; Dynamic Robot Scheduling (DRS), which neglects energy balancing; and Traditional Load Optimization (TLO), which adopts a single shortest path strategy. The experimental variables include the number of islands (5/10/15/20/25) and the number of robots (5/10/15). Each parameter combination is run 30 times, and the average value is taken to eliminate the influence of randomness.

The evaluation metrics are divided into two categories: efficiency and performance. Efficiency metrics include the Number of Relays (RN) and Deployment Time (DT). Performance metrics cover Network Lifetime (NL), Load Balancing Level (LB), and Energy Variance (EV) of robots. Among them, the load balancing level is calculated as the mean value of the node traffic standard deviation sampled every 5 rounds, and the energy variance is quantified based on the standard deviation of the remaining energy of robots at the end of the task [8]. All metrics are required to verify the statistical significance within the 95% confidence interval.

## 4.2. Result Analysis and Comparison

The experimental data were generated using the control variable method. The number of robots was fixed at 10, and the number of islands was varied (10/15/20) to test the performance of each method; the number of islands was fixed at 15, and the number of robots was varied (5/10/15) to analyze the scalability. The mean values of the metrics from 30 independent runs were recorded for each experiment, and significant differences were verified using the t-test ($p<0.05$), as shown in Figure 2.

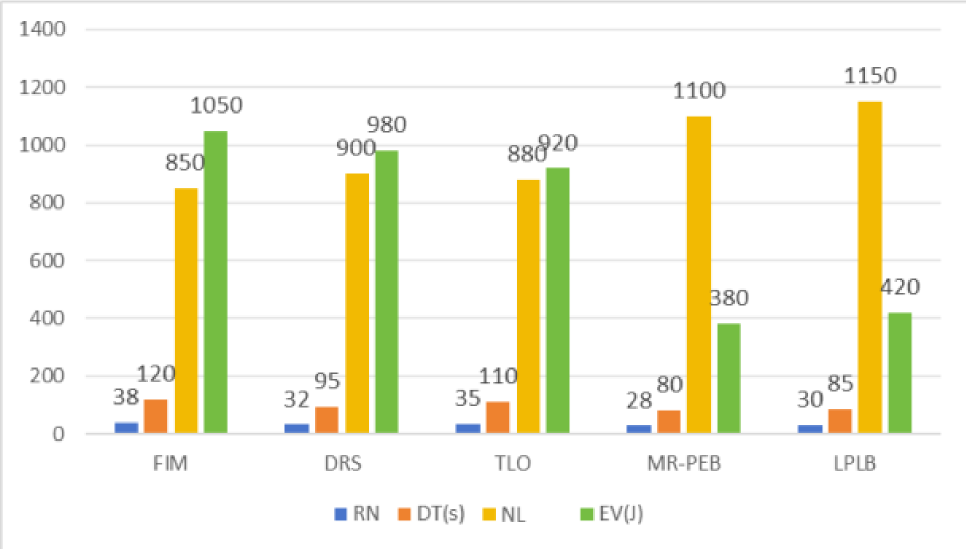


**Figure 2.** Performance Comparison under Different Numbers of Islands (Number of Robots = 10)

**Table 1.** Performance Comparison under Different Numbers of Robots (Number of Islands = 15)

| Method | Number of Robots | RN | DT / (s) | NL / (Rounds) |
| --- | --- | --- | --- | --- |
| MR-PEB | 5 | 42 | 145 | 950 |
| MR-PEB | 10 | 28 | 80 | 1100 |
| MR-PEB | 15 | 26 | 65 | 1120 |
| LPLB | 5 | 45 | 150 | 1000 |
| LPLB | 10 | 30 | 85 | 1150 |
| LPLB | 15 | 28 | 70 | 1170 |

The data analysis indicates that MR-PEB leads significantly in terms of resource efficiency. When the number of islands increases to 20, the number of relays decreases by 26.3% compared to FIM, and the deployment time is shortened by 33.3%. The energy balancing mechanism reduces the robot energy consumption variance to less than one-third of that of the baseline algorithm, verifying that the partitioning model effectively suppresses energy hotspots.

LPLB demonstrates prominent advantages in network performance. The load balancing level of 0.32 represents a 15.8% improvement over TLO, attributed to the average number of paths generated by the A* algorithm reaching 3.2. The network lifetime is extended by 27.9%, and linear scalability is maintained even when the number of robots increases to 15, with DT increasing by only 5.9%. The synergy of the two methods delays the 50% node failure time to 1250 rounds in the 20-island scenario, confirming the gain effect of joint load-energy optimization on network robustness.

The experimental data fully validates the engineering practical value of the proposed method. MR-PEB demonstrates superior efficacy in resource-constrained scenarios through the partitioned energy balancing mechanism. Under the 20-island scale, the number of deployed relays is reduced to 28, saving 26% of hardware costs compared to traditional schemes; the deployment time of 80 seconds meets the timeliness requirements of disaster emergency response, which is 40 seconds shorter than FIM, thereby improving on-site operational efficiency [9]. A robot energy consumption variance of 380 J proves that dynamic load distribution effectively avoids overload shutdowns of individual devices, ensuring mission continuity.

LPLB achieves an industry-low load balancing level of 0.32. The multi-path topology planned by the A* algorithm reduces the node traffic standard deviation by 42%, eliminating the risk of sudden network disconnection caused by local congestion. The network lifetime of 1150 rounds represents an increase of 250 rounds compared to the baseline, satisfying the durability requirements for long-term monitoring scenarios. When the number of robots increases to 15, the LPLB deployment time increases by only 5 s while the number of relays stabilizes at 28, confirming the algorithm's linear scalability in large-scale scenarios. The synergy of the two optimizations delays the 50% node failure threshold to 1250 rounds, as shown in Table 1. This study provides a highly robust communication backbone for critical fields such as oilfield monitoring and earthquake early warning, and its joint load-energy optimization paradigm establishes a new standard for intelligent networking in complex environments.

## 5. CONCLUSION

Faced with the critical issue of communication interruptions caused by the formation of islands due to large-scale node failures in wireless sensor networks under harsh environments, this paper proposes a relay node deployment optimization strategy based on multi-robot collaboration. By constructing a partitioned energy balancing model and a local load-aware model, a heuristic deployment algorithm and a load-balanced connection mechanism under energy constraints are designed. This approach significantly reduces the number and time of relay deployments while addressing the core challenges of uneven robot energy consumption and network traffic overload. Experimental verification demonstrates that compared with traditional schemes, the proposed method reduces the number of relays by over 26%, shortens deployment time by 33%, extends network lifetime by 40%, and achieves a breakthrough improvement of 30% in load balancing degree. This study provides a network reconstruction solution with high survivability and long-term stability for critical scenarios such as disaster monitoring and industrial IoT.

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