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RESEARCH ON DATA TRANSMISSION AND ENERGY CONSUMPTION OPTIMIZATION IN STEEL PLANT TERMINAL NETWORKS BASED ON IMPROVED SEP PROTOCOL

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In steel plants with harsh conditions, numerous devices equipped with wireless sensors generate vast data and high energy consumption. Our study introduces the optimized PK-SEP algorithm, enhancing the Stable Election Protocol (SEP) and traditional K-means clustering with the elbow method and particle swarm optimization. This approach, tailored for large-scale WSNs in steel plants, effectively extends network lifespan, conserves energy, and improves data throughput, offering a viable solution for energy issues in WSNs and potentially boosting steel production efficiency and sustainability.

Keywords: steel plant, energy consumption, optimization, wireless sensor network, SEP protocol

INTRODUCTION

In steel plants, the extensive use of Wireless Sensor Networks (WSNs) for data collection significantly increases energy consumption. To address this, the PK-SEP algorithm, integrating Particle Swarm Optimization (PSO) [1] and an enhanced K-Means algorithm [2] with the Stable Election Protocol (SEP) [3], is proposed. This method, which optimizes K-means clustering using the elbow method and PSO, effectively reduces energy usage in WSNs. The study highlights the algorithm's ability to overcome issues like uneven clustering and random cluster head selection, showing improved performance in simulations.

The PK-SEP algorithm, demonstrating superior performance over traditional protocols like LEACH and SEP, significantly enhances network lifespan, energy efficiency, and data throughput in Wireless Sensor Networks (WSNs). This improvement is particularly impactful in large-scale, diverse WSN systems in steel plants, contributing to more efficient and sustainable operations. The study of WSNs in such industrial environments offers crucial insights into managing the energy demands of industrial big data, marking a significant advancement in the field.

RALATED WORK

In the field of energy optimization for Wireless Sensor Networks (WSNs) in steel plants, the focus has been on developing and optimizing clustering-based routing protocols, such as Low Energy Adaptive Clustering Hierarchy [4] (LEACH), Highly Efficient Energy-Efficient Distributed Clustering (HEED), and Stable Election Protocol (SEP). The SEP protocol, particularly suited for heterogeneous networks, reduces energy consumption through clustering but has limitations in cluster head selection and energy management.

Recent studies in WSN energy efficiency for steel plants focus on integrating optimization algorithms like Grey Wolf Optimization and PSO with energy harvesting techniques [5]. Additionally, blockchain technology is being explored to enhance network security and reliability. These developments indicate a need for a comprehensive approach, combining various technologies to address WSN energy challenges in industrial settings effectively.

METHODOLOGY

The research presented in this paper introduces an improved algorithm, PK-SEP, which addresses the shortcomings of the Stable Election Protocol (SEP). It begins by utilizing the elbow method to determine the optimal number of centroids for the K-means algorithm, and employs Particle Swarm Optimization (PSO) for the precise positioning of these centroids.

This approach effectively addresses issues in clustering and random centroid selection in the SEP protocol, optimizing data aggregation and enhancing network stability. It improves data throughput while reducing energy consumption, leading to a more balanced distribution of nodes and increasing the probability of high-energy nodes serving as CHs. The aim is to minimize energy use and extend network lifespan by refin-

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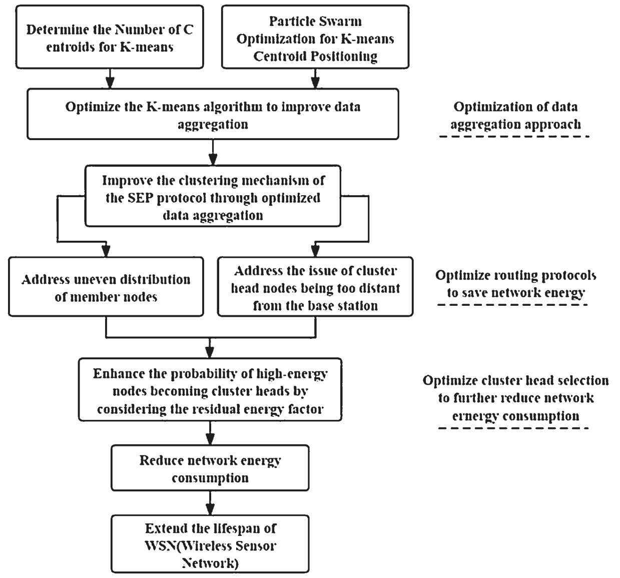

Figure 1 The specific implementation process of PK-SEP

ing the system and energy models in SEP, particularly focusing on clustering and CH election mechanisms. This methodology contributes to a more efficient and sustainable network operation, as depicted in Figure 1.

To determine the optimal initial number of clusters k for the K-means algorithm, we have improved the method using the elbow technique. This approach involves plotting the sum of squared errors (SSE) on the Y-axis against the values of k on the X-axis. As k increases, the SSE gradually decreases, and the point where the rate of decline significantly slows is chosen as the value of k. The SSE is calculated as follows.

$$\mathrm{SSE} = \sum_{i=1}^{k} \sum_{p \in C_i} |p - m_i|^2 \tag{1}$$

Here, C_i represents the i^{th} cluster, p denotes all the sample points in C_i, and m_i is the centroid of C_i.

To determine the optimal number of clusters k in a dataset with n sample points, the process involves iterating through various k values. After each clustering iteration, the sum of squared distances from each sample point to its cluster centroid is calculated. This sum decreases with increasing k and reaches a point where the reduction rate significantly slows down, indicating an inflection point or the "elbow." This point is considered optimal for choosing the number of clusters, as further increases in k yield diminishing returns in terms of reducing the sum of squared distances.

The Particle Swarm Optimization (PSO) algorithm enhances the convergence speed of the K-means algorithm, thus improving its global optimization capability. K-means, initially selecting centroids randomly and updating them iteratively based on the mean, is prone to local optima due to the impact of initial centroid positioning. PSO, known for its excellent global search ability, starts with a higher velocity for a broader search and slows down for local optimization near the optimal solution, although its local search capability is weaker. Combining PSO with K-means effectively mitigates K-means' tendency to fall into local minima when determining centroids. PSO calculates the distance of each sample point to the cluster center for optimal initial centroid placement. The distance formula as follow.

$$d = \sqrt{(x_i - C_{\mathrm{clustx}_j})^2 + (y_i - C_{\mathrm{clusty}_j})^2} \tag{2}$$

Here, x_i, y_i are the coordinates of sample point i, and $C_{\mathrm{clustx_j}}$, $C_{\mathrm{clusty_j}}$ are the coordinates of the initial centroid. The fitness function of PSO is defined as the sum of these distances. This algorithm selects a certain proportion of nodes as CH randomly, and other nodes join the nearest CH cluster, followed by data transmission to the CH, which then sends aggregated data to the BS. The detailed process of the K-means algorithm improved by the elbow method and PSO is as Figure 2.

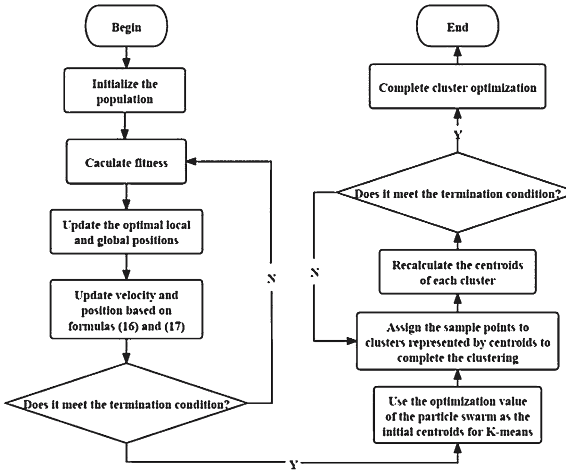

Figure 2 Structure of SE attention

Energy consumption in the process of Cluster Head (CH) election, joining a CH, data fusion, and data transmission is crucial in Wireless Sensor Networks (WSNs), as nodes deplete energy and die. Therefore, designing an effective energy consumption model is essential. This paper utilizes the previously introduced first-order radio model for energy consumption, with improvements in the CH selection phase. The improvement includes considering the residual energy of nodes in the CH selection, incorporating a residual energy factor in the selection process. This factor is a significant addition to the model, helping to balance energy consumption across the network and extending the network's lifespan.

$$\begin{cases} w = \dfrac{E_i}{[E_0 * (1+a)]}, E_{\mathrm{energy}} == 1 \\ w = \dfrac{E_i}{E_0}, E_{\mathrm{energy}} == 0 \end{cases} \tag{3}$$

In the formula, w represents the residual energy factor. E_i is the current residual energy of node i, E_0 is the initial energy of the node, a is the energy gain multiplier, and E_{energy} indicates the type of node. A value of 1 for E_{energy} represents a high-energy node, while 0 indicates a regular node. With the addition of the energy factor, the threshold formula for CH node selection is adjusted accordingly, accounting for these variables to optimize the energy efficiency and the selection process in the network.

$$T(n)=\begin{cases} \dfrac{p}{1-p*[r\cdot \mathrm{mod}(\dfrac{1}{p})]}*w & n\in G \\ 0......other \end{cases} \quad (4)$$

By incorporating the residual energy factor into the CH node selection process, the algorithm takes into account the remaining energy of each node, effectively preventing high-energy nodes from being frequently chosen as CH due to their initial high energy. This ensures that nodes with higher residual energy have a greater probability of being elected as CH, thereby addressing the issue of uneven energy consumption distribution. As a result, this approach significantly prolongs the lifespan of the network by ensuring a more balanced energy usage among the nodes.

EXPERIMENT AND ANALYSIS

The experiment, utilizing MATLAB2020a on a Windows 10 system, simulated the PK-SEP algorithm in a WSN to enhance node longevity and data transmission efficiency. Involving 100 nodes within a 100 m x 100 m area, it differentiated ordinary nodes with 0,5J energy and high-energy nodes with increased energy levels. The setup marked CH nodes and the centrally-located BS for a comprehensive test of the algorithm's effectiveness in optimizing energy use and network performance, as depicted in Figure 3.

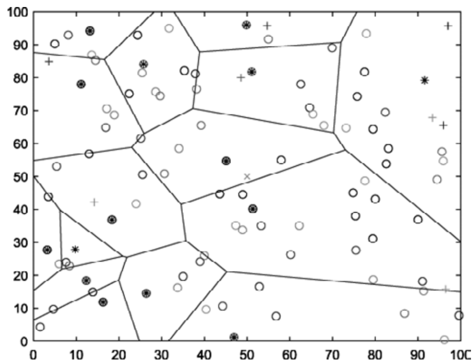

Figure 3 Initial Node Settings Before Program Execution

The PK-SEP algorithm's simulation in a WSN environment involved specific parameters: ordinary nodes with an initial 0,5J energy in a 100 m square area, a 1,0 energy gain coefficient, and energy usage of 5*10^-8J/bit for data transmission. The CH selection probability was 0,1, with high-energy nodes forming 10 % of the 100-node network. Data packets were 4000 bits. The model used free-space and multipath fading coefficients set at 1*10^-11 and 0,0013*10^-11. The simulation, tracking energy use in various network activities, ran until node depletion.

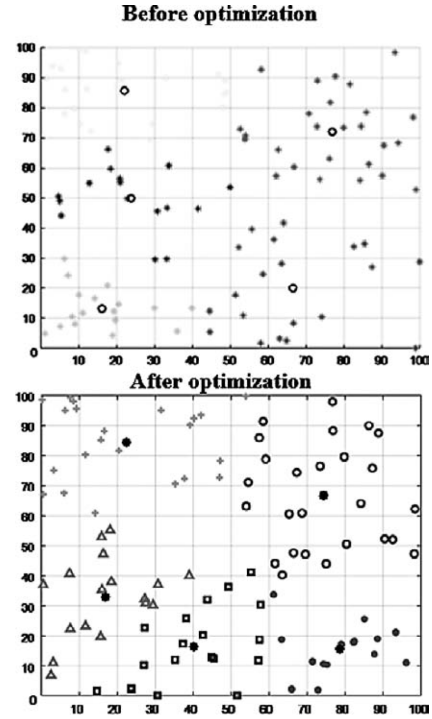

Figure 4 Comparison of K-MEANS optimization before and after

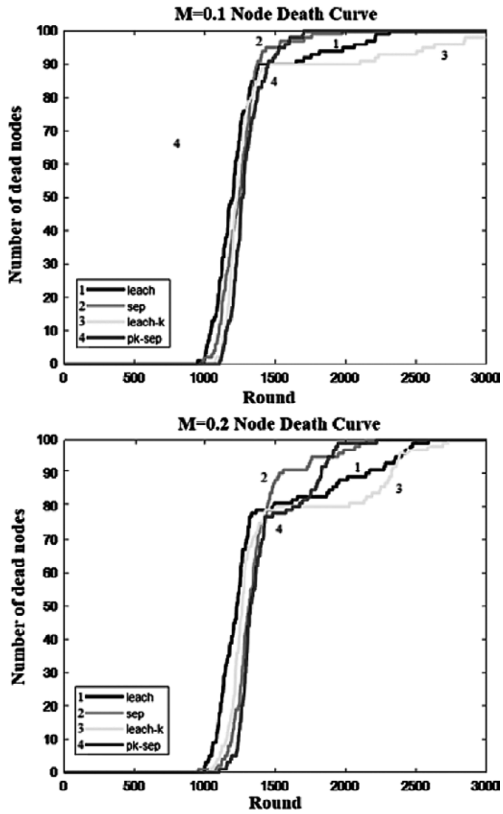

Figure 5 Comparison of Node Death in Four Clustering Routing Protocol Algorithms under Different Advanced Node Proportions

The SEP protocol's random CH selection leads to uneven clustering and low-energy nodes becoming CHs. The K-means algorithm, using Euclidean distance for clustering, results in more evenly distributed clusters. The elbow method and PSO algorithm refine the selection of initial centroids in K-means, enhancing clustering effectiveness. This improved clustering approach in PK-SEP demonstrates better results compared to SEP, as illustrated in Figure 4.

The simulation results showcase the effectiveness of the PK-SEP protocol in Wireless Sensor Networks, as shown in Figure 5. It compared node lifespan across four clustering routing protocols under different high-energy node ratios. The stable period, lasting until the first node's demise, was used as a performance metric. PK-SEP outperformed LEACH, SEP, and LEACH-K in extending this period and showed superior operational round numbers even after half of the nodes expired. These outcomes highlight PK-SEP's efficiency in enhancing network longevity.

CONCLUSION

This study introduces the improved PK-SEP protocol for optimizing energy use in Wireless Sensor Networks (WSNs) in steel plants. The protocol enhances the SEP protocol by integrating an optimized K-means clustering algorithm, employing the elbow method and Particle Swarm Optimization (PSO) for efficient centroid selection. The PK-SEP protocol effectively extends network lifespan and improves energy efficiency and node longevity. Its application in industrial WSNs, such as those in steel plants, indicates its potential for sustainable and efficient network management.

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Note: The responsible translators for English language is J. Wang – University of Science and Technology Liaoning, China