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A Comparative Study of Fitness Function Variants for Energy-Efficient Clustering in Wireless Sensor Networks*

Levente Filep[a], Zoltán Gál[b]

[a]University of Debrecen, Debrecen, Hungary
filep.levente@inf.unideb.hu

[b]University of Debrecen, Debrecen, Hungary
gal.zoltan@inf.unideb.hu

Abstract

Wireless Sensor Networks (WSNs) are essential to a range of applications, including environmental monitoring, smart agriculture, and industrial automation. These networks comprise distributed sensor nodes that collect, process, and transmit real-time data. A significant challenge in WSN design and operation is the limited energy source of sensor nodes (SN); these are usually battery-powered and are often deployed in environments where frequent maintenance or battery replacement is impractical. Transmission energy is proportional to the distance, meaning the further a node must transmit, the more power it must use. A popular strategy to mitigate this problem is clustering. Such techniques classify nodes into clusters, with designated cluster heads (CHs) responsible for aggregating and transmitting data to a central base station (BS), which significantly reduces overall communication overhead and global transmission energy. However, the performance of such clustering methods is highly dependent on the following key elements: determining the optimal number of clusters and the placement of cluster heads. Overall, this can be formulated as an optimization problem.

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Swarm Intelligence (SI) algorithms [1] take inspiration from the behaviors observed in natural swarms, offering practical metaheuristical algorithms for solving complex optimization challenges, including WSN optimizations [2]. These rely on so-called Fitness Functions ($\mathcal{F}$), through which they evaluate the quality of candidate solutions.

Several $\mathcal{F}$ have been formulated and published in the literature for determining optimal CH locations. These proposals range from variations in balances between intracluster and CH-BS (base station) distances to combinations of these distances, residual energy, and energy consumption. Formulated as a single-objective optimization problem, these combinations are usually weighted, allowing them to be adjusted according to specific needs.

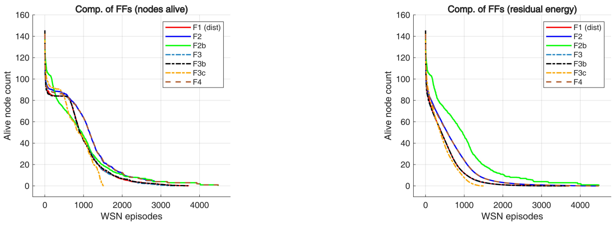
Problem 1 (Fitness function direct comparison)**.** *Although numerous SI algorithms have been proposed for WSN clustering, most studies focus on algorithmic variations while employing similar or slightly modified $\mathcal{F}$. To the best of our knowledge, a direct comparison of FF formulations within identical WSN scenarios remains largely unexplored.*

Problem 2 (Fitness function weight adjustment)**.** *Weights are inherently scenario-dependent. In a dense WSN, a higher intra-cluster distance dependency might be more favorable, while in a sparse WSN, a higher impact of the energy component can be more beneficial. To eliminate the dependency on empirically selected weighting coefficients, the $\mathcal{F}$ can be reformulated in a weight-free manner by normalizing the distance cost with respect to energy.*

We examined several $\mathcal{F}$ formulations from the literature. $F1 = 0.5f1 + 0.5f2$ is purely distance-based, where $f1$ and $f2$ denote the maximum inter- and intra-cluster distances. $F2$ and $F2b$ combine distance and energy terms: $F2 = \alpha f1 + \beta f2 + \gamma f3$, with $f3$ representing the CH energy consumption, while in $F2b$ $f3$ is the reciprocal of the total residual CH energy. $F3$, $F3b$, and $F3c$ are weightless formulations of the form $distance/E_{res}$, using respectively summed distances, worst-case distances ($f1$, $f2$), and their normalized values. Since transmission energy is proportional to distance, we also evaluate $F4$, defined as the total required energy per episode for the proposed CHs.

We ran the simulations on a 200 m x 200 m grid of 150 SNs, using the PSO algorithm. We simulated each $\mathcal{F}$ 10 times and collected results per episode. The CH election was executed every 10 episodes or whenever a CH depleted its energy. Below, we present a brief overview of some results.

Figure 1 shows the average number of active (alive) nodes (a) and the residual (remaining) energy E_{res} of the WSN. We observe that the total E_{res} in the WSN is the highest with the use of F2, since most of the scattered SNs have already depleted their energy and become inactive, thus reducing the load on CHs. Furthermore, F2 manages to keep more SNs alive at the beginning; however, the penalty is a sharp drop in their number after episode 350. The WSN performed worse with F3c, with the network lifespan failing to reach even 1600 episodes.



(a) No. of alive SNs. **(b)** Total residual energy.

Figure 1. Efficacy of $\mathcal{F}$ on WSN comparison.

The number of episodes before all SNs deplete their energy is widely considered the de facto metric within WSN optimization. Although a network with a single or a few alive SNs can technically be considered an active network, its sensing efficacy is debatable. For instance, with F2 in one run, from episodes 3150–4480 less than 3 nodes are active. Results of the analysis are compressed in Table 1.

Table 1. $\mathcal{F}$ performance by percentage (active SNs)

SNs alive		F1	F2	F2b	F3	F3b	F3c	F4
75%	μ	10.10	7.20	**30.30**	9.20	9.70	17.90	6.90
	σ	5.07	0.79	16.48	4.44	(6.68)	18.46	0.74
50%	μ	707.70	**822.40**	450.20	714.20	714.00	569.10	807.70
	σ	22.06	27.29	28.80	28.06	22.02	27.80	38.02
25%	μ	1106.90	1284.50	1128.30	1090.50	1083.80	1094.30	**1291.20**
	σ	32.15	12.90	14.75	27.40	21.11	4.08	18.27
10%	μ	1532.30	1826.90	1719.60	1522.00	1568.20	1370.40	**1839.90**
	σ	49.73	41.43	27.57	45.85	35.62	20.83	31.96

Overall, we found that the weightless formulations of F2 performed significantly worse than their weighted counterparts. The best performing ones were those that included an actual calculation of the required transmission energy. While these were the best, they are also the most computationally intensive.

References

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