Knowledge base tuning by particle swarm optimization for centralized wireless sensor network clustering algorithm

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***Abstract*—Wireless Sensor Networks are integral to various Internet of Things applications [1], where energy efficiency and adaptive data routing significantly influence overall performance. Among different methods, clustering appears as one of the most suitable for efficient energy management [2]. This paper reviews CFC3PSO, a centralized fuzzy clustering method enhanced by particle swarm optimization to dynamically adjust rule weights within a fuzzy rule-based system. By considering multiple input parameters and adapting the knowledge base of the fuzzy rule-based system at the base station across different network life phases, the proposed method outperforms traditional and recent clustering strategies in simulations while dealing with the high amount of uncertainty of these kind of approaches. The results in multiple deployment scenarios demonstrate substantial gains in key performance metrics in wireless sensor networks.**

***Index Terms*—wireless sensor network, particle swarm optimization, fuzzy logic, clustering**

I. Introduction

Wireless Sensor Networks (WSNs) are pivotal in Internet of Things (IoT) environments such as healthcare, smart cities, industrial automation, and precision agriculture. These networks comprise numerous battery-powered sensor nodes, where energy efficiency is crucial to operational longevity. Clustering is a common strategy for energy conservation in WSN. Clustering consists of grouping nodes around other nodes selected as cluster heads (CHs). These CHs receive the information for other nodes, aggregate and send the aggregated data to a central node called base station (BS). Thus, this article discusses CFC3PSO [3], a novel centralized clustering approach that combines fuzzy rule-based systems (FRBS) and particle swarm optimization (PSO) to improve network performance and service life. In CFC3PSO, due to the intrinsic uncertainty of these kinds of system and, consequently, the difficulties to set up the semantic rules of a knowledge base (KB) base for a FRBS, an optimization process is carried out to obtain the weights to apply for each rule of KB to maximize the performance of the network.

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II. CFC3PSO clustering method summary

CFC3PSO uses a Type-1 Mamdani fuzzy inference system to evaluate the suitability of each node to become a CH based on five input variables:

- Distance to the base station (dBS)
- Centrality (C) which is calculated based on the distance of the nodes in a CH to the center of the sensing area of their cluster.
- Node degree (ND) represents the number of neighbors that each node has within a given distance.
- Residual energy (RE) of the node.

- Cluster head rotation frequency (CHR) informs about the number of times a node has been selected as a CH [4].

Each input is fuzzified using three triangular membership functions. The system output, which indicates the likelihood that a node will become a CH ($chance$), is represented using 11 triangular fuzzy sets.

The knowledge base consists of 243 fuzzy rules (3 sets per 5 inputs). Initially, each rule is equally weighted. The novelty lies in the dynamic weighting of these rules, optimized for three different network life cycle stages:

1) Initial phase: from startup to first node death (FND).
2) Intermediate phase: from FND to when half of the nodes are dead (HND).
3) Final phase: from HND to last node death (LND).

In order to achieve rule weights that would be applied to a wider number of different wireless sensor network layouts, the optimization process uses three typical scenarios whose details can be found in Section III.

The tuning process employed a particle swarm optimization (PSO) strategy, referred to as PSO rule weight tuning (PSO-RWT). PSO was used due to its fast convergence, which makes it suitable and widely used in other clustering methods in WSN [5]. The PSO-RWT algorithm is employed to optimize the weight of the rules in the three phases enumerated above. In order to obtain the best FND value, the PSO-RWT is applied to 30 different network layouts, 10 for each of the scenarios described in Section III. Therefore, a set of rule weights is obtained and applied to the clustering algorithm from startup until the first node depletes its battery. Following this, the process is repeated twice: firstly from FND to HND, and then from HND to LND. This is done to obtain the intermediate weights and the weights that maximize the lifestime of the network.

Once the optimization process is complete, the rule weights are loaded into the BS that runs the clustering algorithm. The weights of the rules are then changed according to the stage of the network.

III. Simulation Scenarios

Three test scenarios were developed, each involving a square area measuring 100 × 100 m2, with 100 nodes randomly placed within this area. The primary distinction between these scenarios lies in the BS location, as outlined below:

- Scenario 1: BS at corner of the sensing field
- Scenario 2: BS outside the sensing area at (150, 50) m.
- Scenario 3: BS in the center (50, 50) m.

Each scenario includes 30 different deployments of the 100 nodes, with the same initial energy. The simulations use the first-order radio model detailed in [6]. Table 2 in the original article details the values of the setup parameters for the energy model.

IV. Comparative Evaluation

In order to assess the CFC3PSO, its performance was compared against that of four pre-existing clustering algorithms:

- LEACH: A distributed and probabilistic CH selection method [6]. LEACH is used just as a pattern because it is a well-known clustering method.
- CHEF: Uses residual energy and local density as fuzzy inputs [7]
- CRT2FLACO: Combines Type-2 fuzzy logic with ant colony optimization [8]
- ICUU: Applies the silhouette index and DBSCAN for intelligent clustering [9]

Performance metrics evaluated included:

- FND (First Node Dies).
- HND (Half of the Nodes Dead).
- LND (Last Node Dies).

Tables 4–6 in the original article summarize the results [3]. In all scenarios, CFC3PSO outperformed the other algorithms in all three metrics. For instance, in Scenario 3 (central BS), CFC3PSO achieved an FND of 1847.2 rounds compared to LEACH's 764.8, and an LND of 2344.7 versus LEACH's 1020 rounds.

V. Conclusion

The CFC3PSO approach presents a powerful method for energy-efficient CH selection in WSNs. Its use of a dynamically adapted fuzzy knowledge base, tuned through PSO for different network lifespans, significantly boosts performance. It offers a robust, computationally manageable solution that adapts well to diverse deployment scenarios.

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