A Tuned Fuzzy Logic Relocation Model in WSNs Using Particle Swarm Optimization

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***Abstract*—In harsh and hostile environments, swift relocation of currently deployed nodes in the absence of centralized paradigm is a challenging issue in WSNs. Reducing the burden of centralized relocation paradigms by the distributed movement models comes at the price of unpleasant oscillations and excessive movements due to nodes' local and limited interactions. If the nodes' careless movements in the distributed relocation models are not properly addressed, their power will be exhausted. Therefore, in order to exert proper amount of virtual radial/angular push/pull forces among the nodes, a fuzzy logic relocation model is proposed and by considering linear combination of the presented performance metric(s)(i.e. coverage, uniformity, and average movement), its parameters are locally and globally tuned by particle swarm optimization(PSO). In order to tune fuzzy parameters locally and globally, PSO benefits respectively from nodes' neighbours within different ranges and all the given deployed area. Performance of locally and globally tuned fuzzy relocation models is compared with one another in addition to the distributed self-spreading algorithm (DSSA). It is shown that by applying PSO to the linear combinations of desired metric(s) to obtain tuned fuzzy parameters, the relocation model outperforms and/or is comparable to DSSA in one or more performance metric(s).**

Keywords*—*WSNs, node relocation, force-based movement algorithms, fuzzy logic, particle swarm optimization.

I. INTRODUCTION

As promising surveillance, detection and tracking solutions for many applications, wireless sensor networks (WSNs) are becoming more available and ubiquitous in recent years [1], [2]. The geared movement ability in solo or group in different formations [3], [4] gives the tiny nodes more flexibility especially in harsh and hostile environments. In such environments central control seems to be infeasible for the currently deployed nodes. Unbalanced node formations in the harsh and hostile environments with unexpected node failures can neither be easily mended by manually relocation of currently deployed nodes nor be repaired by redeploying new nodes in the field. Thus, different distributed strategies inspired by nature and physics laws [5], mainly aimed to relocate currently deployed nodes to their new positions. Although distributed node relocation models obviate the need for centralized and manual intervention in network, due to the nodes' local interaction, they suffer from undesirable oscillations and newly formed small coverage holes. Thus, in different distributed node relocation algorithms [6], [7], [8], [9], [10], there is a tendency towards reducing nodes' unnecessary movements and consumed energy in mobile nodes.

Deduced exerted push/pull forces based on fuzzy logic is shown to be a promising model in terms of coverage, uniformity and movement [10] for distributed node relocation algorithms due to the uncertain nature of distributed movement and their local interactions. Finding proper tuned fuzzy parameters of aforementioned performance metrics for currently deployed nodes and at the same time keeping the complexity and computation overhead low in nodes are worthy to be examined. In the proposed model, fuzzy parameters are tuned using particle swarm optimisation (PSO) technique with the small number of iterations. For smooth interactions among the nodes, fuzzy and radial members are chosen from gaussian, t-shape and s-shape functions in contrast to triangular shapes [10]. Parameters are tuned locally in each node with a given *circular zone range* ($R_{zone} \geq R_c$) around the fraction of nodes randomly selected with uniform distribution ($N_{sel} \leq N_{total}$). Then the performance is compared with result found by those tuned globally over the region. The proposed model performance in different boundary strategies and different fuzzy angular/radial movement algorithms similar to [10] is compared with *distributed self-spreading algorithm (DSSA)* .

The main idea is to enable each node to autonomously obtain its fuzzy parameters and to keep the complexity overhead low such that the linear combination presented metrics are optimized via *particle swarm optimization (PSO)* techniques. To the best of our knowledge, there are only a few papers that have considered the proposed approach. The performance of proposed model in terms of percentage of coverage, uniformity, average movement for locally and globally tuned fuzzy parameters are compared. It is shown that performance of model for locally tuned parameters obtained from the fraction of deployed nodes is comparable with global tuned parameters in which all nodes and whole deployed field considered by PSO. In section II related work is briefly presented. In Section III, method and assumptions and in section IV and V respectively performance metrics and result are presented. Finally in section VI, conclusion and possible future work are presented.

II. Related Work

A large proportion of relocation and movement algorithms in the literature [3], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15] are devoted to currently deployed nodes in order to give the network more flexibility, swiftness to react autonomously in the environments where centralized control and supervision are not feasible. Each of these algorithms are aimed at different and overlapping goals such as network connectivity [13], lifetime [12], re-alignment of unbalanced deployments [7], coverage increase [7], recovery of small and large scale coverage holes [6], [9], [14]. However, these algorithms more or less would be able achieve other than their primary objectives. Thus, the performance and efficacy of these algorithms should also be investigated for applications other than their primary design goals. As most algorithms partially inspired and evolved from each other, it is hard to draw fine line between them. They can be mainly classified into *virtual force-based* (radial [7], [16] or angular [13]), *voronoi-based* [14] and *flip-based* [6] movement algorithms. Among these algorithms in WSNs, the amount of unnecessary movements, oscillations and power exhaustion of nodes with local interactions in the distributed relocation algorithms especially with a harsh and hostile environments with lack of central supervision and operation should be reduced as possible. In order to save nodes' power and to localize movement to a specific area in the network, relocation algorithm can be applied to a selected set of nodes [17], [18], fully or partially to avoid unnecessary node oscillations or energy consumption caused by careless movement strategies. Reduction in overhead and delay of centralized relocation paradigm comes at the price of increased *uncertainty* among autonomous nodes who have local interactions within their ranges.

Although fuzzy logic relocation model shown to be candidate solution to address such a uncertainty for the autonomous moving nodes [10], among indefinite choices, proper and justifiable fuzzy parameters and membership functions should be selected. In proposed model, the proper fuzzy parameters in fuzzy logic relocation model can be obtained by applying PSO technique locally with different ranges and globally over the given deployed area. similar to [10] with different angular, boundary conditions and movement strategies, the efficiency and performance of the given model in terms of coverage, uniformity and movement are also compared with *distributed Self-Spreading Algorithm (DSSA)* [7] which benefited from expected global node density.

III. Methods and Assumptions

With the given sensing range R_s and transmission range R_c, sensor nodes are modeled as unite disk graphs (UDG) and are bi-directionally connected when they reside within their one another's ranges. Nodes are randomly deployed in 2D rectangular field of $[x_{min}\ x_{max}] \times [y_{min}\ y_{max}]$ with the uniform distribution. Nodes' locations are known by either centralized or distributed localization algorithms [19], [20]. *Circular zone* around the node is defined as a circle with radius of R_{zone} ($R_{zone} = k \cdot R_c$) with the node in the center of circle and are used to obtain the fuzzy parameters from nodes' neighbours residing in the given zone via PSO.

TABLE I: Fuzzy Rules [10]

(a) Pair Radial Force System

Distance	Pressure
Very Far	No Action(0)
Far	Pull hard(-1)
Moderate	Pull(-0.5)
Close	Push(0.5)
Too Close	Push Hard(1)

(b) Pair Angular Force System

Distance	Pressure
Very Far	Hard(1)
Far	Medium(0.75)
Moderate	Slow(0.5)
Close	Very Slow(0.25)
Too Close	Nothing (0)

TABLE II: Membership Functions

z-function
$f_z(x;a,b) = \begin{cases} 1, & x \le a \\ 1-2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 0, & x \ge b \end{cases}$
Symmetric Gaussian function
$f_g(x;\sigma,\mu) = e^{\frac{-(x-\mu)^2}{2\sigma^2}}$
s-function
$f_s(x;c,d) = \begin{cases} 0, & x \le c \\ 2\left(\frac{x-c}{d-c}\right)^2, & c \le x \le \frac{c+d}{2} \\ 1-2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2} \le x \le d \\ 1, & x \ge d \end{cases}$

A. Fuzzy Logic Parameters

Fuzzy rule-based systems are applied in a variety of research areas [21], [22]. For fuzzy control problems Takagi-Sugeno (TS) [21] rule based systems briefly are described as follows:

$$\begin{aligned} \text{Rule R}_j: \ & if\ x_1 \ \text{ is } \ A_{j1} \text{ and} \cdots \text{and } x_n \ \text{ is } \ A_{jn} \\ & then \ \ y_j = a_{0j} + a_{1j}x_1 + \cdots + a_{nj}x_n \end{aligned} \tag{1}$$

where $x = (x_1, x_2, ..., x_n)$ is an n-dimensional input, A_{nj} is a fuzzy membership and y is a non-fuzzy output. Fuzzy rule base system's output is calculated from the following equation,

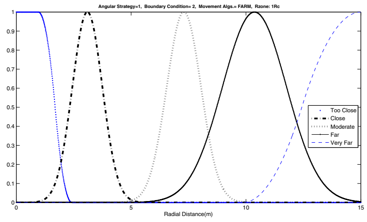
$$y = \frac{\sum_{j=1}^{p} \mu_j(x) \cdot y_j}{\sum_{j=1}^{N} \mu_j(x)}, \tag{2}$$

$$\mu_j(x) = \mu_{1j}(x) \otimes \mu_{2j}(x) \otimes \cdots \otimes \mu_{nj}(x) \tag{3}$$

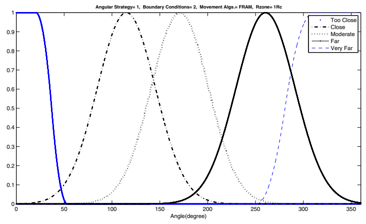
p is the total number of rules. Similar to [10] two different fuzzy inference systems are used: *fuzzy radial pair force* and *fuzzy angular force*. Both fuzzy radial pair force system and fuzzy angular force system have one input as distance with 3 gaussian functions, one z-function and one s-function memberships (Table II) and one crisp output, pressure which can take the fuzzy values push hard, push, no action, pull and pull hard. The rules of these systems are listed in Table I. Membership function parameters a, b, c, d, μ, σ computed using particle swarm optimization. Figure 1 is brought as the example of respectively tuned radial and angular membership functions for angular strategy A_1, boundary condition B_2 and movement strategy $FRAM$. Hence, fuzzy parameters can be tuned using particle swarm optimization with regard to linear weighted combinations of metrics in terms of percentage of coverage, uniformity, and average movement equation 4.

$$F^* = argmax_F\{w_1 \cdot C(F) - w_2 \cdot U(F) - w_3 \cdot M(F)\} \tag{4}$$

w_1, w_2, w_3 are respectively weights for coverage (C), uniformity (U), and average movement (M). F is a set of fuzzy parameters tuned by PSO with regard to the performance weights. Thus, parameters can be tuned based on one or linear combination of the metrics. The negative and positive signs



(a) Radial Membership



(b) Angular Membership

Fig. 1: Radial and Angular Membership function

used where performance metrics should be minimized (i.e. movement, uniformity) or maximized (i.e. coverage) respectively. In order to tune parameters PSO is applied in two different *global* and *local zone range* which are as follows: In *global* range, PSO applied on all deployed nodes over whole 2D rectangular field ($[x_{min}\ x_{max}] \times [y_{min}\ y_{max}]$) while in *local zone-range*, proportion of nodes N_{sel} from set of deployed nodes N_{total} ($N_{sel} \leq N_{total}$) are randomly selected with uniform distribution. PSO is applied for each selected node with a zone-range of R_{zone} ($R_{zone} = k \cdot R_c$) around selected node by taking account node's neighbours residing within its R_{zone} range. It should be noted that in both local and global ranges, boundary conditions are considered in tuning fuzzy parameters.

B. PSO structures

In this paper, the constriction coefficient PSO used similar to the [23]. Thus,in this approach the velocity update equation is as follows:

$$v_{ij(t+1)} = \chi \left[v_{ij(t)} + \phi_1 \left(y_{ij(t)} - x_{ij(t)} \right) + \phi_2 \left(\hat{y}_{ij(t)} - x_{ij(t)} \right) \right] \quad (5)$$

y_{ij} is the particle best and $\hat{y}_{ij}$ is the global best particles and,

$$\chi = \frac{2k}{\left| 2 - \phi - \sqrt{\phi(\phi - 4)} \right|} \quad (6)$$

with $\phi = \phi_1 + \phi_2, \quad \phi_i = c_i r_i \quad i = 1, 2$. Equation 6 is used under the constraint that $\phi \geq 4$ and $k, r_i \in [0, 1]$. The parameter k in the equation 6 controls the exploration and exploitation. For $k \sim 0$, fast convergence is expected and for $k \sim 1$ we can expect slow convergence with high degree of exploration [23]. Each particle consists of two arrays, which one is related to the memberships of the pair force fuzzy systems and another one is related to the memberships of the angular force fuzzy systems. Each fuzzy system has 5 memberships and each membership is specified by its mean and variance, therefore each array has 10 cells.

C. Boundary Strategies

In relocation algorithm, behaviour of moving nodes while approaching to the given area's boundaries (i.e. $[x_{min}, x_{max}] \times [y_{min}, y_{max}]$) with respect to different boundary conditions should be taken into account. Boundary strategies applied in [10] are adopted here which are *non-stop at boundary*, *stop at boundary*, *wrap around*. (B_1)-In non-stop at boundary, regardless of boundaries of given area, nodes relocate towards their new locations without limit. (B_2)-In stop at boundary, nodes stop at boundaries of given area and their movements are limited if their new computed locations are beyond the area boundaries. (B_3)-In wrap around, according to toroidal surface, nodes are wrapped around to other (opposite) sides if new computed locations go beyond the area boundaries.

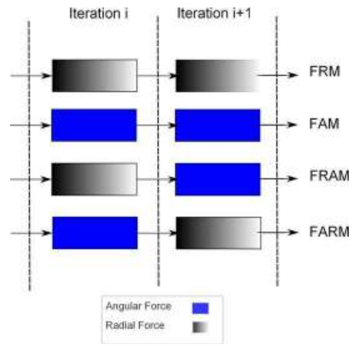


Fig. 2: Fuzzy Node Movement Algorithms [10]

D. Angular Force Strategies

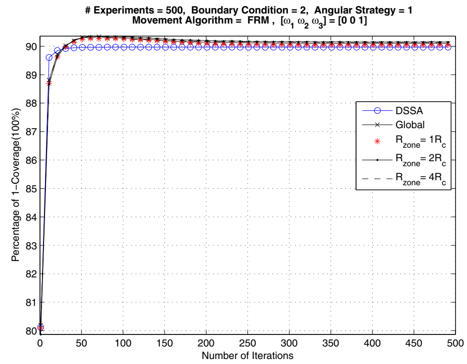
Force exerting node n_{fv} is considered as vertex of angle $\angle\alpha = (n_1, n_{fv}, n_2)$ $(0 < \alpha \leq 180°)$ with each pair of its neighbours n_1,n_2. Angular force strategies in [10] based on exerted forces from node's neighbours can be considered as:(A_1)-*Smallest Angular Movement* Strategy, among exerted angular forces from node's neighbours, the one is selected that causes smallest node angular movement. (A_2)-*Closest Neighbour Movement* Strategy, among exerted angular forces from nodes' neighbours, the closest neighbour is selected as the exerting angular nodes.

E. Fuzzy Node Movement Algorithms

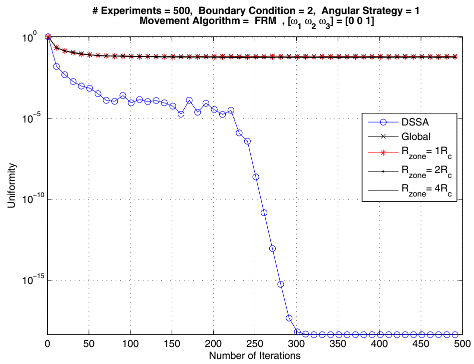
In our model, similar to [10], fuzzy node movement algorithms are as: *Fuzzy radial movement* (FRM)- Nodes are mutually affected by radial force from their neighbours. The amount of node movement is related to overall push/pull virtual forces from their in-range neighbours. *Fuzzy angular Movement (FAM)*- Nodes exert a force to their in-range neighbours depending on aforementioned angular force strategies. *FRM then FAM (FRAM)*- FAM is applied to result of FRM in consecutive iterations. (Figure 2). *FAM then FRM (FARM)*- FRM is applied to the result of FAM in consecutive iterations (Figure 2).

IV. Performance Metrics

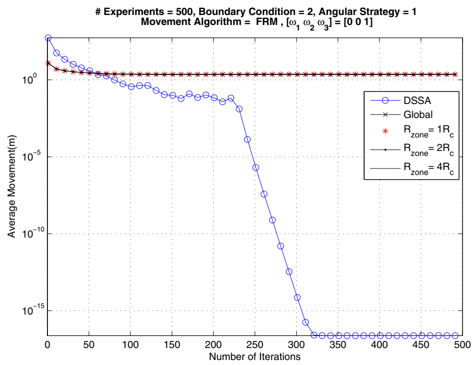
The performance metrics presented are: *Percentage of Coverage(C)*-Suppose that a 2-D rectangular area of $[x_{min}, x_{max}] \times [y_{min}, y_{max}]$ is divided into grid cells. The coverage of the given grid cells is defined as the number of nodes covering the cells' corner coordinates z_i=(x_i, y_i). Thus, *percentage of 1-coverage* is defined as the ratio of grid cells within range of at least one sensor node to the total number of area's grid cells. This metric illustrates how an efficient relocation algorithms are able to cover the given area. *Uniformity (U)*-The measure of nodes being uniformly



(a) Percentage of 1-Coverage,(A_1,B_2,FRM)



(b) Uniformity,(A_1,B_2,FRM)



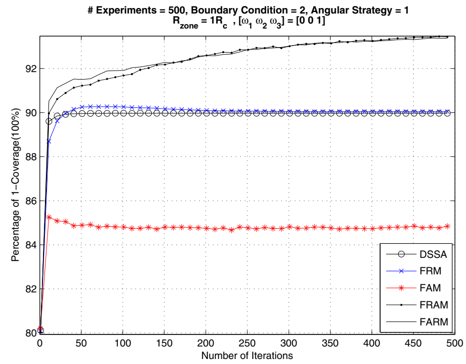
(c) Average Movement,(A_1,B_2,FRM)

Fig. 3: Performance Comparison of Relocation Algorithm for globally and locally (R_{zone}={1,2,4}$\cdot R_c$) Tuned fuzzy parameters

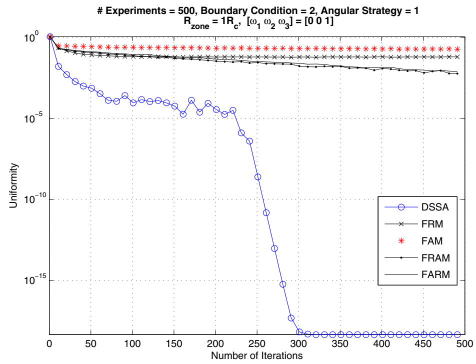
distributed is defined in [7]. U is defined as the average local standard deviation of internodal distances [7].

$$U_i = \left(\frac{\sum_{j=1}^{k_i} (D_{i,j} - M_i)^2}{k_i} \right)^{1/2}, U = \frac{\sum_{i=1}^{N} U_i}{N}, \tag{7}$$

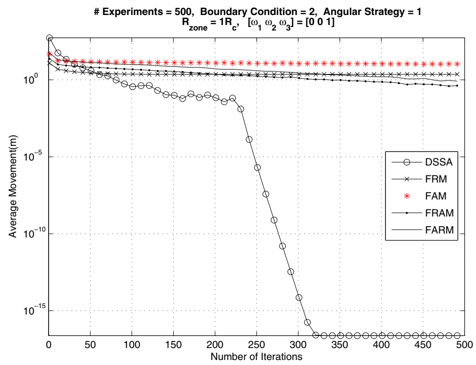
where N is the total number of nodes, k_i is number of neighbours of the ith node, $D_{i,j}$ is the distance between the ith and jth nodes, and M_i is the mean internodal distance between the ith node and its neighbours [7]. *Average Movement (M)* - It is defined as total movement of nodes in each iteration over the number of nodes in the given iteration. As movement is related to amount of node's consumed energy, average



(a) Percentage of 1-Coverage



(b) Uniformity



(c) Average Movement

Fig. 4: Performance of Different Movement Strategies with Boundary condition B_2 and Angular Force Strategy A_1

movement of nodes in each iteration represent a suitable metric for comparison of various node relocation algorithms in the context of energy efficiency.

V. Results

The proposed node relocation algorithm was simulated by Matlab and N=100 nodes with the transmission and sensing range of R_c=R_s=15 are distributed uniformly in the rectangular 2-D space of $[-100\ 100] \times [-100\ 100]m^2$. The fuzzy parameters are obtained locally as $N_{sel} = 30$ of total deployed nodes $N_{tot} = 100$ are randomly selected with zone ranges of R_{zone}=$(1, 2, 4)\cdot R_c$. The fuzzy parameters are tuned via particle swarm optimization ($k = 0.5$, $c_1 = 3$, $c_2 = 3$ equation 6) with boundary conditions of B_1, B_2, B_3 and angular strategies of A_1 and A_2. The membership parameters are also obtained globally in rectangular field of

$[-100\ 100] \times [-100\ 100] m^2$. By tuning fuzzy parameters both globally and locally (R_{zone}=$(1, 2, 4) \cdot R_c$) by PSO, relocation algorithms were simulated 500 times and 500 iterations for different boundary conditions and angular strategies. For the sake of brevity and page limit, only the result based on tuned fuzzy parameters with $(\omega_1, \omega_2, \omega_3) = (0, 0, 1)$ (Equation 4), with zone range R_{zone}=$1 \cdot R_c$ and A_1 and B_2 and movement algorithm of FRM are presented in Figure 3. The rest of the results more or less follow the same trends.

The performance of the all movement strategies with R_{zone}=R_c and A_1 and B_2 (N_{sel}=30, $N_{tot} = 100$) is compared to DSSA (Figure 4). In Figure 3, as R_{zone} reduces, performance degrades. Figure 3 also shows that even when PSO is applied locally to zone range of R_{zone}=R_c and for 30% of total nodes, performance still is comparable to the case where PSO is applied globally on all the nodes over the whole given area. Figure 3 also shows that proposed model either outperform or is comparable to DSSA for different movement strategies, even DSSA benefits from expected global node density. Since for each node, tuned parameters are obtained once in the first iteration and do not change in remaining iterations, proposed model still has acceptable performance with regard to DSSA. Figure 4 shows FRAM and FARM have the best percentage of 1-coverage, FAM has the worst percentage of 1-coverage and FRM has a comparable performance to DSSA. With regard to uniformity and average movement FRM, FAM, FRAM, and FARM have similar performance and are comparable to DSSA. It should be noted that depending on different linear combinations of weights (ω_1,ω_2, ω_3) (Equation 4), performance of relocation algorithms with different movement strategies FRM, FAM, FRAM and FARM can vary.

VI. Conclusion and Future Work

A tuned fuzzy logic relocation model is proposed in which its fuzzy parameters are tuned either globally or locally via particle swarm optimization technique so proper amount of virtual forces can be exerted on nodes. The results show that our proposed model either outperform or closely matches the performance DSSA in terms of percentage of coverage, uniformity and average movement even the tuned parameters are obtained locally within nodes' transmission range R_c. As a possible extension, by using light PSO computations, instead of only the first relocation iteration, fuzzy parameters can continuously be tuned and modified in consecutive iterations in each node according to the neighbours behaviour in the given iteration.

Acknowledgment

This research was supported by the Australian Research Council (ARC) discovery research grant No. DP0879507.

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