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Fuzzy Based Composite Metric Approach to Control Redundant Sensors in Wireless Sensor Network

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Abstract: Wireless sensor network is the collection of sensors grouped together to perform a specific task. The sensors are placed either in a regular pattern or in a random manner. In contrast to regular deployment, random deployment may lead to the existence of redundant sensors, used to monitor the same field of interest. The redundant sensors may degrade the network performance in many aspects such as energy consumption, coverage, connectivity, etc. In this study the tradeoff between the number of active sensors, coverage, energy and connectivity is discussed in detail. Parameters such as connectivity, number of neighbors and distance towards the sink and coverage overlap are put into fuzzy logic system. The output measure, namely, Node Selection Probability (NSP) from the fuzzy inference system decides whether or not the sensor nodes should be redeployed and need to be alive or inactive. Simulation results show that the algorithm effectively extends the network life time and has achieved high throughput, residual energy and coverage with reduced number of sensors. The number of sensors are reduced by eliminating the redundant sensors which will produce the maximum redundant effect.

Key words: WSN, redundancy, fuzzy, redeployment, selection

INTRODUCTION

The main components of wireless sensor networks are sensor nodes (used as source, sink/actuators) gateways, internet and satellite link, etc., which are shown in Fig. 1. Sensor nodes are the network components will be sensing and delivering the data. Each node has a communication range which defines the area in which another node can be located in order to receive data. This is separate from the sensing range and this area can be observed by a node. The two ranges may be equal but are often different (Mulligan and Ammari, 2010). All the data collected by the sensors are forwarded towards the sink and are accessed by the users in the outside world. The number of sink may be single or multiple depending on the underlying application.

Sensors are used in a wide range of applications like environmental monitoring, wildlife monitoring, security, smart agriculture system, continuous health monitoring, target tracking, transportation, entertainment, etc. These applications require various levels of sensing profile. The main functionality of sensor nodes are sensing, computing and communicating. A sensor node by itself has severe resource constraints such as low battery power, limited signal processing limited computation and communication capabilities and a small amount of memory.

One of the solutions to overcome such constraints is to deploy the sensors in an efficient manner. Inclusion of all such constraints together is a difficult task. The difficult part in wireless sensor network is the framing of its infrastructure where the sensors may be deployed randomly or deterministic way. In random deployment, the nodes are placed randomly in any order by using airplane or helicopter where human cannot be able to reach the target area. In regular or pre-deterministic way the exact location of sensors are predetermined and the sensors are deployed accordingly. Some of the available regular pattern for sensor deployment are regular triangle, square, rhombus and equilateral hexagon, Veronoi diagram, Delauny triangulation, etc. Either in random deployment or regular deployment, the functionality of the network gradually reduces as time elapses due to decrease in the number of living sensor nodes so it is necessary to effectively redeploy and maintain on-off state of sensor to improve coverage, achieve load balance and to prolong the network lifetime. To extend the efficient functioning of the network, the various factors such as coverage, connectivity, energy consumption, reliability, network lifetime, sensor redundancy, link availability, average distance between the nodes, mobility of nodes, density of network neighbor topology need to be considered. Some of the optimization

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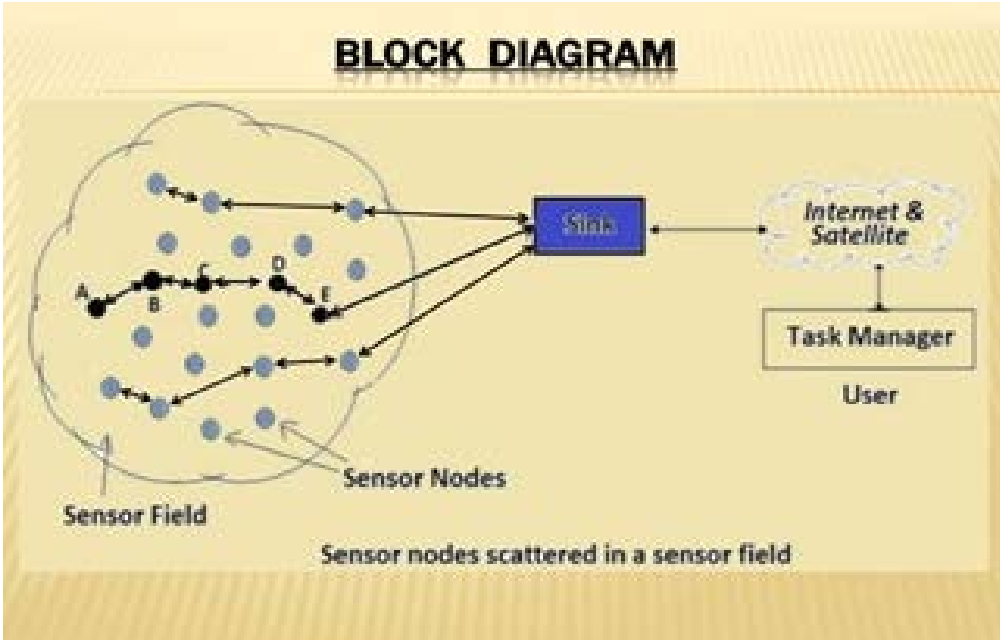

Fig. 1: Main components of the wirless sensor network

techniques such as virtual force method particle swarm optimization simulated annealing, fuzzy logic and genetic Algorithm help to balance these factors and provide fruitful network accessibility.

In WSN, so many research works are carried out in various fields like localization of sensors, deployment of sensors, security, data aggregation, payload balancing, clustering, etc., to produce optimal results. In this research, a fuzzy based decision making system is introduced for identifying the redundant sensors and utilizing the redundant sensors in an efficient manner (Fig. 1).

Redundancy is the provision of additional or duplicate resources which can produce similar results (Luha *et al*., 2014). The amount of redundancy needed or required is one of the major factors influencing almost all strategies designed for WSN. Redundancy in sensor networks is both ally and enemy. The redundancy can be categorized into three types, namely, spatial redundancy, temporal redundancy and physical redundancy. Spatial redundancy is the redundancy due to the replication of resources in the coverage area which leads to the retrieval of information for a specific location from different sources. Spatial redundancy is very practical in WSN and provide large amount of redundancy in network coverage and connectivity. Temporal redundancy also known as time redundancy is used to improve the precision of sensor nodes readings and to endure transient faults in sensing and communication (Curiac *et al*., 2009). Information is related with the duplication in the structure of data exchanged in the network. So, the existence of redundant sensor may lead to any type of redundancy in terms of coverage, connectivity, data, unnecessary energy depletion or bandwidth usage. The network will become either error prone or fault tolerant based on level of redundancy among the sensors. There must be a moderate level of redundancy to produce the better results.

The proposed algorithm using fuzzy inference system comprises of two parts, namely, identification of redundant sensors and elimination of redundant effects. Initially, the parameters such as connectivity, number of neighbors and distance towards the sink and coverage overlap are given as input to the fuzzy inference system. The output metric NSP from the fuzzy system is used to determine the redundancy level of the sensor and categorize the sensor as redundant or not. Later the sensor may be turned off and make it reserved for future use or it may be pushed to the distance of 0.5 RC towards the sink in order to overcome the coverage hole problem to some extent. Also, the proposed system produced fruitful results in the aspect of identifying the redundant sensors in an accurate manner.

Literature review: In wireless sensor network, identification of the best place is important where the sensors can be placed to produce good results. Recently, many of the research are carried out to find an optimal solution for the effective placement of sensors and redeployment if need. After deploying the sensor, both in random and regular deployment, redeployment of sensors is unavoidable due to the possibility of malfunctioning of sensors, exhaust of energy, coverage hole, etc.

Li *et al.* (2015), proposes a distributed Energy balanced VFA (Virtual Force Algorithm) to redeploy the sensors. The energy spent for transmitting the data depends on the distance between the two nodes under communication. An energy control function is used to adjust the virtual force between two nodes to ensure the maximized life of each node so that the lifetime of the entire network would be prolonged obviously. The VFA algorithm calculates the coverage by placing the sensors along the virtual motion path and redeploys the sensor at a location where it finds the maximum coverage.

In order to reduce the energy spends at a node for relaying data packets, it is important to reduce the hop distance between the nodes and the sink. Multiple sinks are placed in the network so that, the sensed data can reach the sink in a limited number of hops which results in decreasing the relay workload in intermediate nodes and latency (Chatterjee and Das, 2015). Multi-sink topologies also offer redundancy and fault-tolerance in case of sink-node failure. The number and the exact locations of the sink nodes directly affects the lifetime of the sensor network (Chatterjee and Das, 2015).

Cheng and Huang (2015), the time taken for redeploying the sensor in the grid based topology is considered. In this research, the redundant energy is calculated for each grid which is the difference between the sum of energy of all sensors in the grid and the average energy of the grid changes with the WSN's operation time 't'. The sensors are sorted in the grid by the remaining energy. The sensor with highest remaining energy is selected for relocation. Relocation is done on the occasion of coverage hole healing and during the malfunctioning of sensors. To improve the response time, cascaded movement is included to have the maximum remaining energy.

The relocation is based on the density of nodes. The density of the network varies based on the number of nearby neighbor within the distance of communication. Based on the density, the force is calculated (Pandita and Upadhyay, 2015). If the network has low density then there will be no force between the nodes. If the nodes are separated by minimum distance then the nodes exert attractive force. The distance for relocation is calculated based on force. By doing so unnecessary movements are reduced so as to prevent the energy consumption and increase the efficiency of the process.

Huang *et al.* (2015) proposes an optima deployment strategy to maximize the lifetime of the network. The factors such as connectivity, coverage and transmission rate are considered to find the place of relocation on emergency. Guohang Huang *et al.* (2015), the deployment strategy is performed by ACO (Ant Colony Optimization) in which an ant is initially located on any point on which a sensor node can cover at least one POI (Point Of Interest). The ant moves from a point to another in search of the POI that can cover more uncovered POI which will in turn improve the coverage of the network. Also, a load balancing deployment mechanism is included to enhance the lifetime of the network.

The study on various deployment techniques implies that redeployment of nodes is a crucial issue. For redeployment the factors like distance, connectivity, coverage, energy density, etc., are considered to enhance the network functionality. In this research for efficient redeployment, a fine tuned fuzzy based decision making system is included by considering the network parameters such as distance towards the sink, number of neighbors, coverage redundancy, connectivity to identify the redundant sensors. Once the redundant sensors are identified, either it may be included or excluded or redeployed to the estimated location. The proposed system was evaluated in the aspect of coverage, residual energy, throughput and it seems to be well performed than the regular deployment

MATERIALS AND METHODS

Problem identification: Since, there is no pre determination in random deployment there may be chances of placing the sensors more or less than the requirement. There will be no uniformity in placing the sensors it leads to extra redundant sensors which may cause wastages of energy, lack in throughput, presence of coverage hole, overhead in data communication and data aggregation and redundancy in coverage.

To overcome these constraints to some extent, a fuzzy based approach is proposed which will analyze the environment using the network parameters and optimal decision is made in the sensor placement strategy. According to the fuzzy decision, the sensor position may be retained without any change or it may be pushed towards the sink to reduce the redundancy level or it may be redeployed to minimize the coverage hole or the extra sensor will be turned off.

System description: Some of the basic assumptions about the environment for the proposed research are stated here.

Area of Interest (AOI): All sensors are distributed in a two dimensional area.

Identification of sensors: Only on knowing the exact location of the sensor, data communication will be feasible. So many techniques are available to provide the location information of sensors to other sensors. In the proposed research, GPS (Global Positioning System) is involved to gather the location information of sensors.

Distribution of sensors: All the sensors are scattered in the AOI in a random manner using air drop method.

Nature of sensors: All the sensors are battery operated and it has sufficient memory capacity to store and forward the sensed information. All sensor nodes can detect the obstacle using ultrasonic module. All the sensors are mobile in nature except sink which is at the center.

Sensing profile: The sensing area of sensors is represented by circle whose radius is equivalent to Sensing Radius (RS). In addition to that sensors have communication radius which is equivalent to Communication radius or Radio Range (RC). The sensors can be able to communicate the sensed information only to the available other sensors in its communication range. All are homogeneous in nature (i.e.,) sensing profile is common to all. In the proposed research, the communication radius is set as twice of the sensing radius (i.e.,) RC = 2RS. Also communication radius can be adjusted based on requirement. The sensors sense the environment and the sensed information are forwarded towards one destination called sink.

Estimation of network parameters

Probability of connectivity (PCON): In wireless sensor network, a collection of nodes are working together to sense and communicate the information. The network is said to be fully connected if there exists at least a path connecting each pair of nodes in the network. Connectivity is a prime factor but it is difficult to achieve the full connectivity due to various factors like mobility, energy, reliability of links, density, communication radius, coverage, etc.

The movement of sensors are not predictable in some of the applications like dense forest or sea which will highly degrade the connectivity. In a large scale fully connected network, the energy required for data transmission increases as number of nodes increases. Also, it is not always necessary to have the network in a fully connected way but with some isolated nodes. There exists a tradeoff between the number of isolated nodes and energy consumption.

The degree of connectivity required for randomly deployed network is still an open issue for all researchers. New techniques are frequently being developed to optimize the multi-faceted trade-offs between parameters like cost, connectivity, energy consumption, coverage, communication range and other application specific issues as needed.

In the proposed research an optimal decision is made to provide the trade-offs between connectivity, number of neighbors, distance towards the sink and coverage overlap. According to percolation theory, some of the well-known mathematical derivation for connectivity is discussed.

Theorem 1 (A probabilistic bound to avoid isolated nodes in homogeneous ad-hoc networks): Given an ad-hoc network with n>>1 nodes and a homogeneous node density ρ in nodes per unit area (Bettstetter, 2002). If anyone wants to be sure with a probability of at least p that no node in this ad-hoc network is isolated, i.e., dmin ≥1, then one can set the radio range (γ) of all nodes to:

$$\gamma \geq \sqrt{\frac{-\ln\left(1-P^{1/n}\right)}{\rho\pi}} \tag{1}$$

Theorem 2: Gupta and Kumar employ results from continuum percolation theory and random graphs to derive a sufficient condition on γ as a function of n. They show that uniformly deployed n nodes in a planar unit area disk, if:

$$\gamma \geq \sqrt{\frac{\log(n)+c(n)}{\pi^2 n}} \tag{2}$$

then the resulting wireless multihop network is asymptotically almost surely connected if and only if $c(n)\to+\infty$. In the proposed work to achieve the desired level of connectivity, the communication range is adjusted as in Eq. 1.

Estimation of Coverage Overlap ($Cov_{overlap}$): It is highly preferable that the target area must be covered fully and it must have enough neighbors to communicate the sensed information. There is a tradeoff between the number of sensors that are to be included or excluded for network operation. The one of the concern for deciding the number of sensors to be included is the desirable coverage ratio. The coverage ratio is the ratio of total area covered by the available sensors to the target area to be covered. Coverage intersection is the area overlapped by one or more neighbor sensors. In this study, the redundant sensors are identified based on the estimated coverage intersection measure. If a sensor is highly overlapped by its neighbor sensors then it is considered as an extra sensor. In practical, it is very difficult to estimate the area intersected by its neighbors because in random deployment the distance and orientation of sensors are not uniform. Research works are carried out to estimate the coverage.

In this study, an efficient way of estimating the area intersected by the neighbor sensors is introduced. The overall algorithm is described below. After the deployment of the sensors randomly their neighbors list is generated. All the sensors are homogeneous having same communication ranges represented by circle. Maximum number of points are randomly generated within the communication circle. The number of points that fall within the communication circle of any one of its neighbors are estimated by calculating the distance between point and the location of its neighbors. If the distance of separation is less than or equal to communication radius, then it is counted as overlapped point. Finally, the coverage overlap ratio is calculated as the ratio of points overlapped by its neighbors to the total number of points generated within the communication circle.

Distances towards the sink: The sensor communicates the sensed information to the access points either continuously or upon receiving the request or during any abnormality. The number of access points and their position may vary based on the underlying application. The sink may be either static or dynamic. Since, all data streams are forwarded to the access points, its position and relative distance to other sensors will produce some impact in data communication process. The inter distance between the neighboring sensors affect the signal strength which in turn influence the energy dissipation for communication. The distance towards the sink is calculated as aerial distance using the distance formula as shown in the equation:

$$\text{Distance} = \sqrt{\left(X_i - X_{SNK}\right)^2 + \left(Y_i - Y_{SNK}\right)^2} \tag{3}$$

Where:

(X_i, Y_i) = Denotes the position of ith node

i = 1, 2, 3, …, n

(X_{SNK}, Y_{SNK}) = Denotes the position of sink Sensing can be improved by enhancing the sensing profile of the sensor. The effective Communication can be achieved with large communication range, desirable number of neighbors and with reachable distance

Alogrithim to calculate coverage overlap area

Input

S:Set of Sensors
N:Set of Neighbours
RC:Communication Rang
n:Total Number of sensors
v:Number of Neighbours
m:Maximum Number of Random Point that can be generate within the Communication Area Represented by circule.
C:Count of overlapped point

Output:

Cov–Aerea–overlap:The percentage of Communication Area of sensor overlapped by its Neighbours Sensors

```
Algorithm
    Start
    Repeat for every sensor S_i in I=1,2,......n
    Initialization C=0
    Genrate K Random Point X_1,X_2,......,X_k Where K=1,2,.....,m
    Repeat for every V Neighbour N_v of S_i
        Repeat for every Random Point
            Find Euclidian distance d_k
            If d_k<Rc then C=C+1
    Estimate Cov_Area_overlap=(C/K)×100
Stop
```

Estimation of effective neighbors (N neigh): Based on the underlying application, the participating sensors may be static, mobile or mixed. In the harsh like environment, employing static nodes are tedious when compared to mobile nodes. However, uncontrollable mobility causes some serious effects such as less connectivity, more energy consumption, variation of routing overhead, network lifetime, stability of the links, etc. which will degrade the overall performance of the network.

In random deployment, the resulting network may be dense or non-dense. The sensor node should have considerable amount of neighbors within its transmission range to maintain the stability. As the data transmission power is proportional to the square of transmission range, power consumption can be minimized by dynamically adjusting transmission range according to the distance with neighboring nodes (Rathod *et al*., 2015).

Each node processes the received data from its group of neighboring sensor nodes and sends that processed data to the base station through multiple hops . The base station is the most critical part of a sensor network as all the relevant data collected by the sensor nodes are directed towards the base station where the data is aggregated and processed. When compared to the farthest nodes, the nodes which are nearer to the sink (Base station) have to transmit more amounts of data because all the messages can be reached the sink only through its neighbors.

Excess number of neighbors cause overhead whereas inadequate number of neighbors will result in data loss. Anyhow, the exact number of required neighbors for an specific application cannot be determined in advance. Kleinrock and Silvester (1978) optimize an objective throughput function based on the average number of neighbors and suggest that a fixed magic number of neighbors equal to six is sufficient to guarantee network connectivity regardless of the value of n. Takagi and Kleinrock (1984) later revised this magic number to eight. Xue and Kumar (2004), the author show that there is no magic number but rather that the number of neighbors required grows as Ôlog n. In particular, they show that this number must be larger than 0.074 log n and >5.1774 log n. Song *et al.* (2005), the researchers show an improved lower bound for the number of neighbors of 0.129 log n.

In practical, the required number of neighbors depend not only on the total number of sensors involved but also some other factors like degree of connectivity, residual energy, available bandwidth, etc. It is not always possible to achieve full connectivity in a large scale and randomly deployed networks. Also, it is not necessary to have full connectivity. To find the range of neighbors in need an optimal decision making system is required.

In the proposed research, the distribution of nodes are not uniform throughout the network. A fuzzy based optimal decision making system is introduced to distribute the sensors in the area of interest in a balanced manner. According to the fuzzy system, the density of sensors near the boundary is less, near the sink is moderate and in the remaining areas is comparatively more. This is done by either turn on or off the extra sensors to eliminate the redundancy or push the sensors to eliminate the coverage hole.

Effects of redundancy: The amount of acceptable redundancy is one of the major factors influencing almost all strategies designed for WSN. Generally speaking, a low rate of redundancy is nearly always unfavorable for the reason that it's extremely error prone. With increasing redundancy, the WSN becomes more and more fault tolerant. In other hand, redundancy also results in wastages of bandwidth in handling redundant data, energy consumption, increased work load, etc. There is a tradeoff between the necessary and unnecessary involvement of sensors for proper functioning of networks irrespective of various applications.

Extra sensors will lead to redundancy in coverage, connectivity, sensed data, etc., it is necessary to make optimal decision about the number of sensors that are to be involved in networks. In the proposed algorithm, the sensor activity is restricted by considering its number of neighbors, distance to the sink and residual energy. Fuzzy based composite metric approach is considered to control the redundant sensors in wireless sensor network.

An effective utilization of network resources is always a critical concern in wireless sensor network because of its resource constraint nature. Several research works are carried out to find an optimal solution for handling the resources. The main aim of the proposed work is to minimize the energy consumption by avoiding the redundant sensors.

The proposed system involves two stages. The first stage is to identify the redundant sensors by analyzing the network parameter values. The second stage uses fuzzy controller to make an optimal decision regarding the action to be taken on identified redundant sensors. The overall structure of the proposed system was given in Fig. 2. For each iteration, the following steps are considered:

Step 1: Randomly deploy the sensors (n) in two dimensional space using air drop method.

Step 2: Gather the location information and estimate the distance to the sink(x_s, y_s) $Dsink_i$ as in Eq. 3

Step 3: Calculate the number of nearby neighbors N_{neigh}, (Near by neighbors of a node are the nodes which are at a distance less than its Communication range) and Coverage area overlapped by neighbors

Step 4: Feed the inputs such as Probability of connectivity (Pcon), Distance to the sink (Dsink), Nearby Neighbors (Nneigh) and the percentage of coverage overlap (COVoverlap) to the fuzzy controller

Step 5: By applying the fuzzy inference mechanism, the Node Selection Probability (NSP) is calculated. Based on NSP the following actions are considered:

Case 1: If the node selection probability is low, then no action is taken for that node

Case 2: If the node selection probability is medium then the sensor will be turned "inactive(off)" mode for that iteration and turned "active(on)" mode for the next iteration.

Case 3: If the node selection probability is high then the sensor will be pushed towards the sink for the distance of 0.5×RC.

Step 6: End.

Fuzzy inference system

Fuzzy controller: Fuzzy logic is an approach computing based on "degrees of truth" rather than the usual "true or

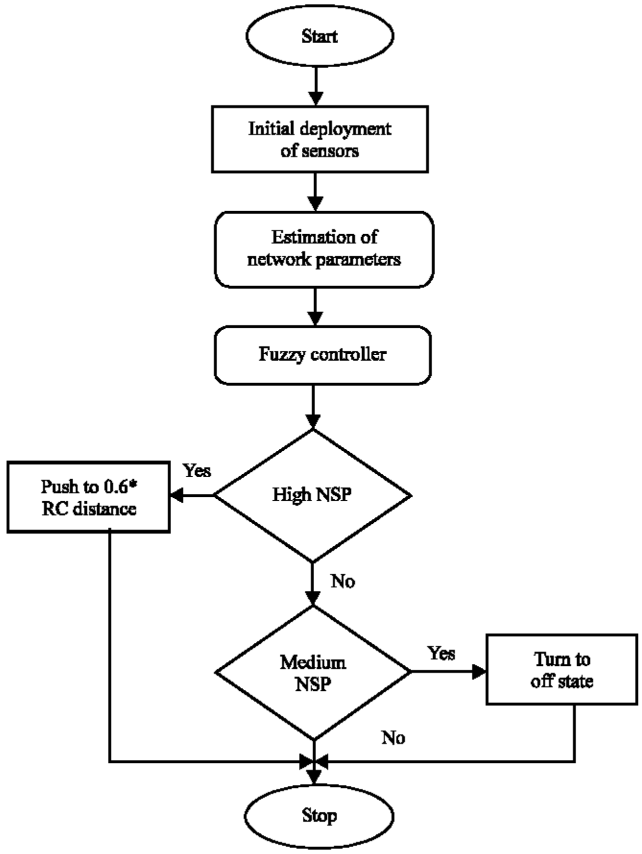

Fig. 2: Overall flow of the propsed system

false "(http://Whatis.Techtarget.Com/Definition/Fuzzy Logic). The main components of fuzzy logic system are fuzzification, rule evaluation, aggregation of the rule outputs and defuzzification which are described below (Jothi and Chandrasekaran, 2014).

Fuzzification: This involves obtaining the crisp inputs from the selected input variables and estimating the degree to which the inputs belong to each of the suitable fuzzy set.

Rule evaluation: The fuzzified inputs are taken and applied to the antecedents of the fuzzy rules it is then applied to the consequent membership function.

Aggregation of the rule outputs: This involves merging of the output of all rules.

Defuzzification: The merged output of the aggregate output fuzzy set is the input for the defuzzification process and a single crisp number is obtained as output Linguistic variables are the input or output variables of the system whose values are words or sentences from a natural language instead of numerical values. A linguistic variable is generally decomposed into a set of linguistic terms. The overall flow of the fuzzy model is shown in Fig. 2.

Membership functions of Input/output parameters: Membership functions are used in the fuzzification and defuzzification steps to map the non-fuzzy input values to fuzzy linguistic terms and vice versa. A membership function is used to quantify the linguistic terms. There are different shapes, namely, triangular, trapezoidal, Gaussian, etc. Among these triangular and trapezoidal are three and four parameterized respectively. By adjusting the parameters related to the membership function, one can fine tune the system within less time. In the proposed fuzzy based decision making system both inputs and outputs are represented by triangular membership function. Table 1 shows the detail about input parameters and their possible values (Fig. 3).

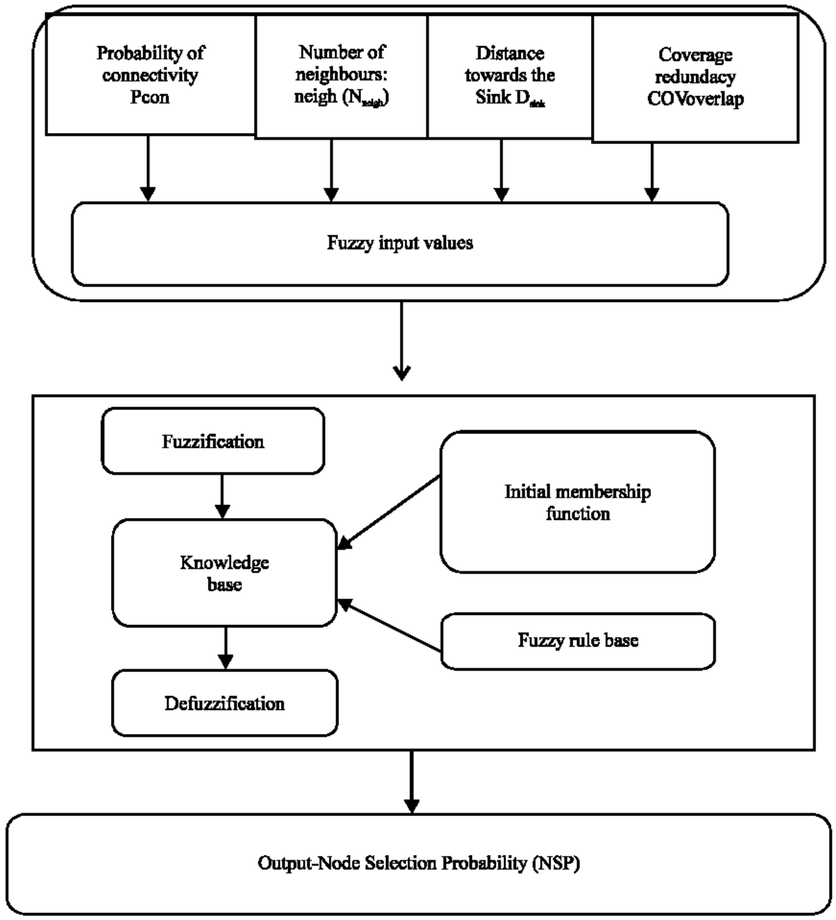

Fig. 3: Fuzzy model of the propsed system

Table 1: Input parameter and their values

Input parameter	Parameter value
Probability of connectivity	Low, Medium
Distance toward the sink	Vnear, Near, Far
Coverage overlap	Low, High
Near by neighbous	Nfav, Fav, Hfav

Table.2: Propesed fuzzy interference rules

S.No	P con	Nneigh	D sink	Cov overlap	Output
1	Low	Nfav	Far	Low	Medium
2	Low	Nfav	Far	High	Medium
3	Low	Hfav	Vnear	High	Medium
4	Low	Hfav	Far	High	High
5	Medium	Nfav	Far	Low	Medium
6	Medium	Hfav	Vnear	Low	Medium
7	Medium	Hfav	Far	Low	High
8	Medium	Nfav	Near	High	High
9	Medium	Hfav	Far	High	High
10	Medium	Hfav	Vnear	High	Medium
11	Medium	Hfav	Near	High	High
12	Medium	Nfav	Far	High	Medium
13	High	Nfav	Far	Low	Medium
14	High	Hfav	Vnear	High	Medium
15	High	Nfav	Far	Low	Medium
16	High	Nfav	Near	High	High
17	High	Nfav	Far	High	Medium
18	High	Hfav	Vnaer	High	Medium
19	High	Hfav	Far	High	Medium

The membership functions for the input parameters are shown in Fig. 4. The membership function of output value (NSP) of the fuzzy module is also shown in the picture below and its language variables are active, off and push (Fig. 4).

Defuzzification: After fuzzification, the input parameters to the fuzzy system are evaluated using inference rules and the inference rules used in the proposed system are mentioned in Table 2. The Column in the table denotes the output parameters and rest of the column represents the input parameters. Fuzzy rules are governing tools for making a final decision on output. The fuzzy rules are written using If then statement. In this proposed system 'AND' operator is used to evaluate the input parameters. For example: if P_{con} is low and N_{neigh} is not-favorable and D_{sink} is Far AND Cov.Overlap is low then the resultant value, i.e., NSP is medium (Table 2). The combined input will result in output distribution. The output distribution is converted into crisp output value using centroid defuzzification methodology:

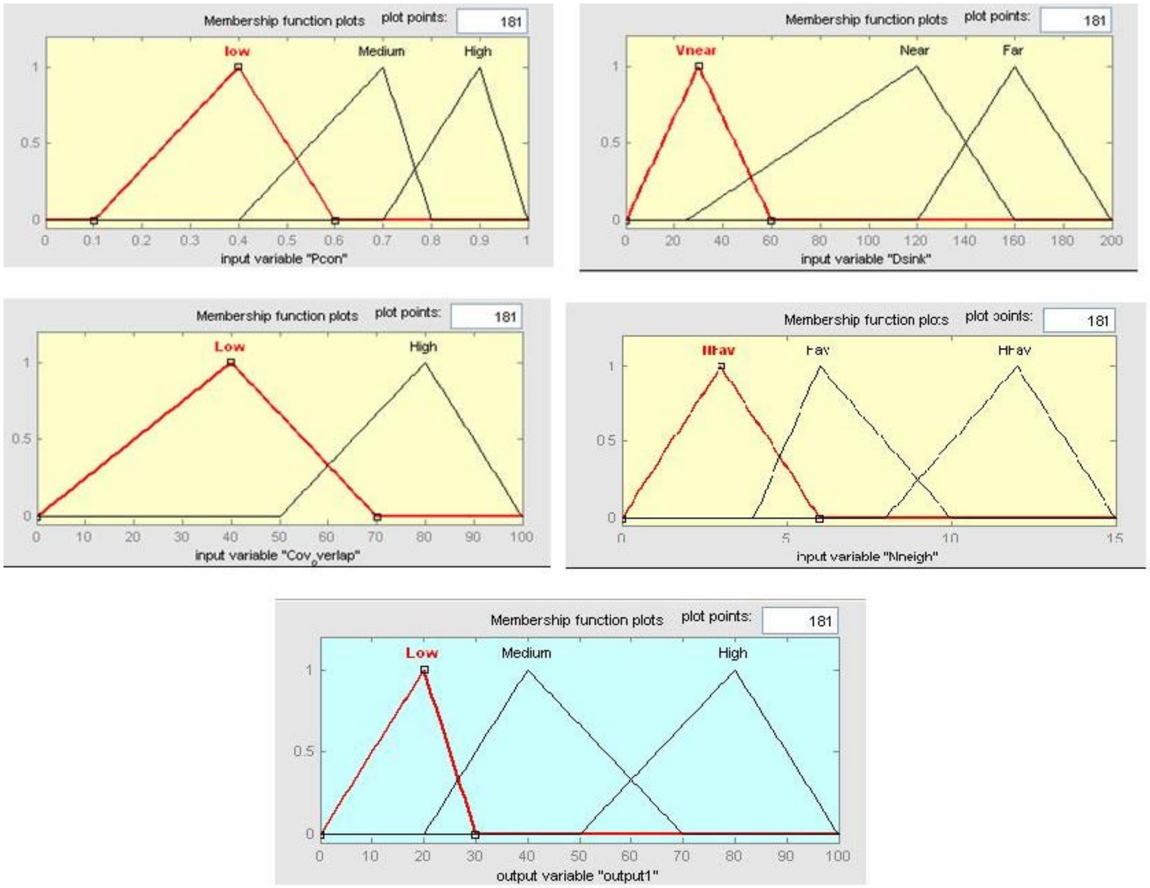

Fig. 4: Membership function for input and output parameters

$$F_{nsp} = \frac{\int \eta_{agg}(f) f df}{\int \eta_{agg}(f) df} \quad (4)$$

where, η_{agg} is aggregated input.

RESULTS AND DISCUSSION

The fuzzy based decision making system was tested and implemented in Matlab R2013. Also, the results are compared with the non-fuzzy system. The metrics used for evaluation are coverage, residual energy, Throughput and number of active sensors. In the proposed fuzzy based system, the redundant effect is tried to reduce by either turn off the extra sensors or push the sensors to the place where there is scarcity. The number of sensors involved for network operation is reduced to some extent. With this minimum count of these sensors, it is able to produce better performance.

In the proposed fuzzy based system, decision on extra sensors are taken by considering the resultant connectivity, number of available neighbors, its distance towards the sink and the area of coverage overlapped by its neighbors. Inclusion of fuzzy based system improves the optimality of decisions taken for inclusion of sensors. Energy constraint is one of the major issues in WSN. By reducing the number of active sensors, one can conserve energy without affecting the functioning of network. Each and every application has its own requirements. Based on its requirements, one can either include or exclude the parameters such as residual energy, SNIR, mobility, etc., to avoid redundancy. The performance of the proposed fuzzy based system reveals that factors like throughput, residual energy are increased, because some of the extra sensors are turned to off. Similarly, the percentage of resultant coverage is increased in the proposed fuzzy based system because some of the extra sensors are pushed to the coverage hole area.

The experiment was conducted by varying the number of nodes, the area of deployment and

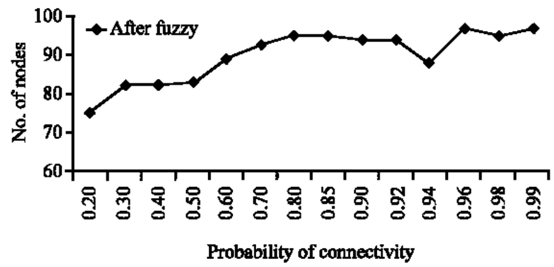

Fig. 5: No. of active sensors vs. probability of connectivity (100 nodes deployed in the area 10000 m^2)

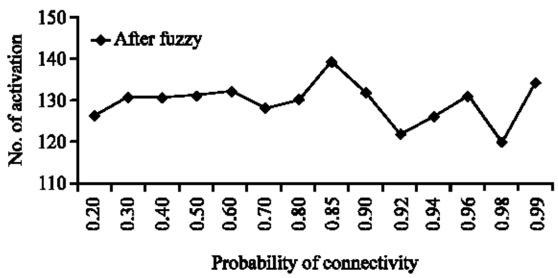

Fig. 6: No. of active sensors vs. probability of connectivity (150 nodes deployed in the area 90000 m^2)

transmission radius to achieve different probability of connectivity. The sink is placed at the center and all the nodes are mobile in nature except the sink. The transmission ranges are varied in order to achieve different probability of connectivity. The mobility is modeled using random way point model. The simulation parameters used in several runs are mentioned in Table 3. The experiment was conducted in different rounds and the resultant data are fed to fuzzy system for fine tuning. The performance of the proposed fuzzy based system was compared with non-fuzzy system it is noted that the proposed fuzzy based system performed well in the aspect of achieving throughput, residual energy and number of active sensors.

Reduction of the number of active sensors: The number of active sensors is the ratio of sum of average of the active sensors to the total number of nodes deployed and the corresponding results are mentioned in Fig. 5 and 6 by applying both fuzzy and non-fuzzy system. The proposed fuzzy based system reduces the number of active sensors by turning the redundant sensors to off. The results conclude that more number of nodes are under control in dense network than small scale network. During low probability more number of nodes are turned to off state when

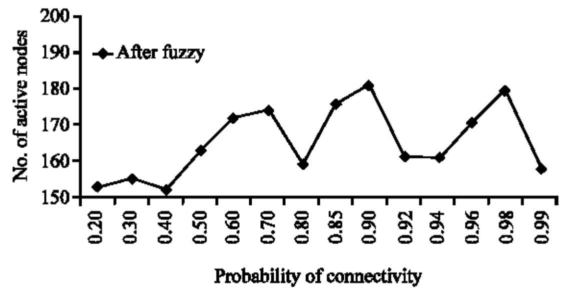

Fig. 7: No. of active sensors vs. probability of connectivity (200 nodes deployed in the area 160000 m^2)

Table 3: Simulation environment-N/W parameters

No. of nodes	Area (m^2)	Transmission radius (m)
50	10000	[15-23]
100	40000	[23-34]
150	90000	[29-43]
200	160000	[35-50]
250	250000	[40-57]
300	360000	[45-63]

compared to medium and high probability of connectivity which affects the throughput in the low probability of connectivity.

The graphs in Fig. 5 and 6 show that out of the total nodes, on an average of >18% of the total nodes are turned to off. In doing so, one can save the energy consumption to some extent. Also, the same sensor can be used in case of any sensor malfunctioning or failure or draining of the energy to prolong the normal functioning of the network.

Figure 5 the number nodes which are remain active during the simulation of 100 nodes deployed in the area of 10000 m^2 is plotted for the different probabilities from 0.2-0.99 by varying the communication radius from 23-34 m as shown in by applying both fuzzy and non-fuzzy system

Figure 5, it is concluded that the number of nodes turned to off is more during the lowest probability, i.e., 18% of the nodes turned to off during the probability 0.2-0.7. The number of active sensors is reduced by 8% during the probability 0.8-0.92 whereas the number of active sensors is reduced by 4% during the probability 0.96-0.99. During the probability 0.94, the number of active sensors is reduced by 12%.

Figure 7, the number of active sensor's results for different probability of connectivity from 0.2-0.99 in simulating the 150 nodes deployed in 90000 m^2 by applying both fuzzy and non-fuzzy system are shown. The probability of connectivity is changed by varying the communication range from 29-43 m. For the probabilities 0.2-0.7, the number of active sensors is reduced by

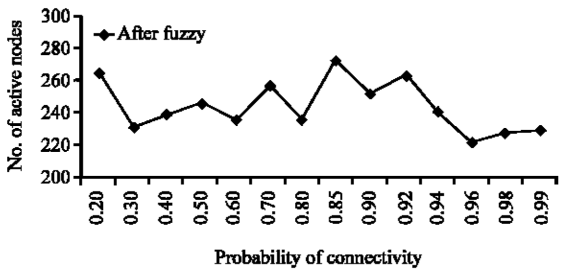

Fig. 8: No. of active sensors vs. probability of connectivity (300 nodes deployed in the area 360000 m^2)

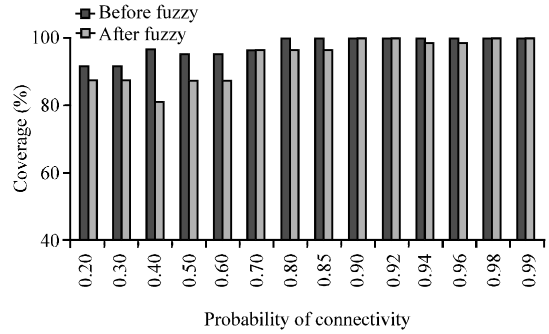

Fig. 9: Probability of connectivity vs. coverage (50 nodes deployed in the area 10000 m^2)

12%. During the probabilities from 0.85-0.99, the number of active sensors is reduced by 20%. The proposed fuzzy based system produces better results when compared to the deployment of 100 nodes in the area 10000m^2. The number of active sensors for different probabilities from 0.2-0.99 is plotted in Fig. 7 on deploying 200 nodes in the area of 160000 m^2 by applying both fuzzy and non-fuzzy system. For the probabilities 0.2, 0.3 and 0.4, the number of active sensors is reduced by 25%. In the probability 0.50, 0.80, 0.92, 0.94 and 0.99, the number of active sensors is reduced by 20% and for the remaining probability, it shows that more or less 10-15% of the total nodes are turned to off.

Figure 8 the number of active sensors on deploying 300 modes in the area of 360000 m^2 is plotted for different probability achieved by varying communication range from 45-63 m by applying both fuzzy and non-fuzzy system. During the probabilities 0.3, 0.4, 0.5, 0.6, 0.8 and 0.94, the number of active sensors is reduced by 20%. The active sensors are reduced by 25% with the probabilities 0.96, 0.98 and 0.99 which is higher than the remaining probabilities.

The proposed fuzzy based system effectively reduces the redundant sensors in the large scale networks, i.e., with 200 and 300 nodes when compared to small scale networks with 50 and 150 nodes. In practical, the topology of the network will not remain same. To enhance the performance, the communication range of the sensor may be varied.

Performance in achieving coverage: Coverage is the measure of total area covered by the active sensors to the total area of interest. Existence of coverage hole may lead to data loss. The fuzzy based system provides a perfect balance between the number of nodes turned to off and the coverage achieved. By involving 80% of the nodes, more than 97% of the coverage in the proposed fuzzy based system is achieved. In most of the cases, the percentage of coverage achieved by the proposed fuzzy based system is found to be higher than the coverage achieved in the non-fuzzy system and it is lesser in few cases. From this point of view, the proposed fuzzy based system effectively reduces the redundant sensors without affecting the coverage. The percentage of the coverage achieved by deploying various nodes in different area are represented in Fig. 9.

The coverage achieved by deploying 50 nodes in the area 10000m^2 and varying the communication radius as given in by applying both fuzzy and non-fuzzy system are plotted in Fig. 9. Accordingly, the coverage achieved with the probabilities 0.9, 0.92, 0.94, 0.96, 0.98 and 0.99 is closer to 100% where as the coverage achieved during 0.4 is only 80%. Also, it is able to achieve 85% coverage with the probabilities 0.2, 0.3, 0.5 and 0.6. One can achieve 90% coverage with probabilities 0.7, 0.8 and 0.9. In the proposed fuzzy based approach, the coverage achieved is satisfactory in most of the probabilities except in few probabilities.

The coverage achieved by deploying 100 nodes in the area of 40000 m^2 and varying the communication radius as given in by applying both fuzzy and non-fuzzy system is given in Fig. 9. The full coverage is achieved with the probabilities 0.90, 0.92, 0.96 and 0.99 whereas nearly 83% coverage is achieved with the probabilities 0.2, 0.30 and 0.4. The coverage 92% is achieved for probabilities 0.5, 0.6, 0.7, 0.8, 0.85 and 0.98.

Figure 10-12 the resultant coverage is plotted on deploying 150 nodes in the area 90000m^2 on varying the communication radius as shown in by applying both fuzzy and non-fuzzy. The coverage of 90% is achieved for all the probabilities except for 0.2 and 0.4. The proposed fuzzy based system produces good results in large scale networks when compared to small scale networks.

Figure 13 shows the coverage achieved by deploying 200 nodes in the area of 160000m^2 by applying both fuzzy and non-fuzzy system. More than the 95% of the coverage is achieved with the probabilities 0.7, 0.8, 0.85, 0.90, 0.92,

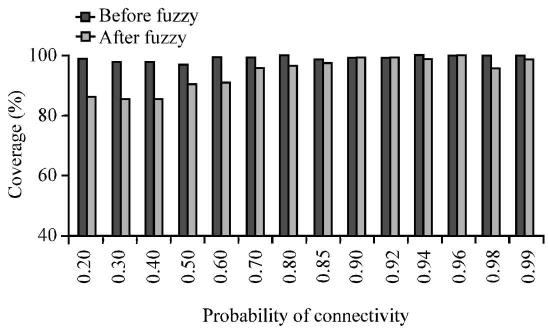

Fig. 10: Probability of connectivity vs. coverage (100 nodes deployed in the area 40000 m^2)

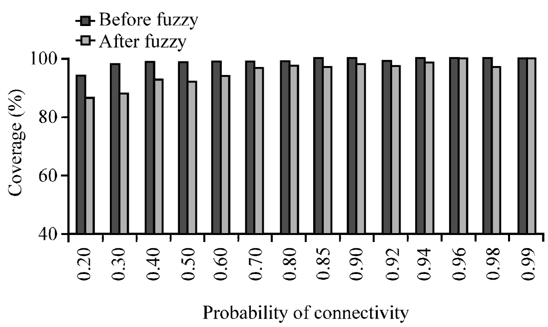

Fig. 11: Probability of connectivity vs. coverage (150 nodes deployed in the area 90000 m^2)

0.94, 0.96, 0.98 and 0.99 whereas 85% of the coverage is achieved when it has probabilities 0.2 and 0.3. For the probabilities 0.4, 0.5 and 0.6, 90% of the coverage is achieved. The proposed fuzzy based system produces comparatively better results.

The coverage achieved by deploying 300 nodes in the area of 360000 m^2 by applying both fuzzy and non fuzzy system is shown in Fig. 13. The coverage achieved with the probabilities such as 0.7, 0.8, 0.85, 0.9, 0.92 and 0.94 is >95%. The coverage 90% is achieved for the probabilities 0.3, 0.4, 0.5 and 0.6. In sensitive applications of sensors, full coverage is always necessary. In order to achieve full coverage, the system must be fine tuned.

Energy conservation: Sensor is a small tiny device with limited capabilities. Once the sensor gets its energy drained then the sensor must be replaced or recharged. Frequent replacement and recharging will drastically degrade the overall performance of the network. Conservation of energy is essential irrespective of the applications. Residual energy of a node is the amount of remaining energy available for a node. The residual energy of the network is the average of the residual energy of all the active sensors in the network. The resultant residual energy of the network with and without fuzzy tuning system were represented in Fig. 14-16.

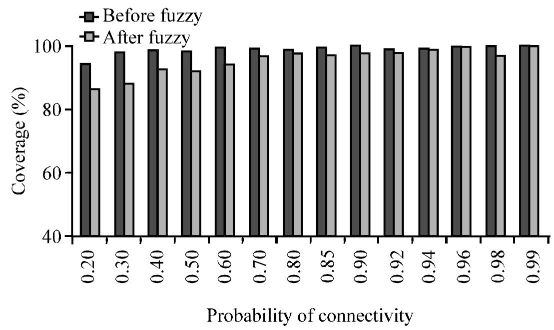

Fig. 12: Probability of connectivity vs. coverage (200 nodes deployed in the area 160000 m^2)

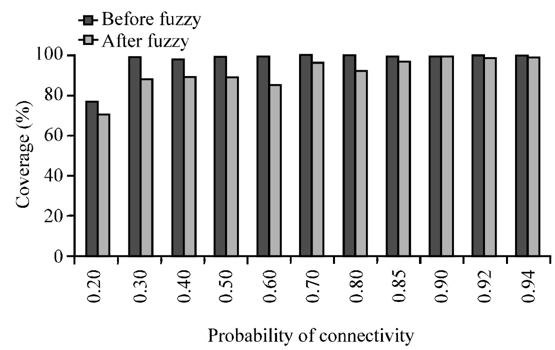

Fig. 13: Probability of connectivity vs. coverage (300 nodes deployed in the area 360000 m^2)

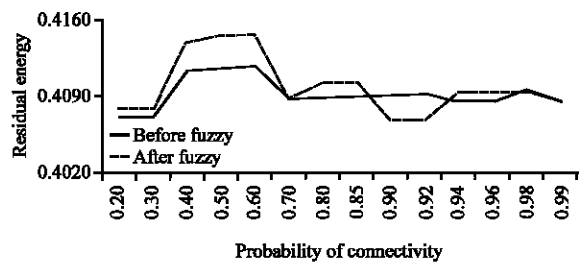

Fig. 14: Residual energy vs. probability of connectivity (50 nodes deployed in the area 10000 m^2)

The resultant residual energy of the network on deploying the 50 nodes in the area 10000 m^2 by applying both fuzzy and non-fuzzy system are given in Fig. 7 for the different probabilities as shown in the Table 3. The residual energy of the network is decreased for the probabilities 0.90, 0.92 and 0.99. The proposed fuzzy based system is able to achieve the increased residual energy of the network in most of the probabilities.

The residual energy of the network on deploying the nodes 150, 200 and 250 in the area 90000, 160000 m^2 and 250000 m^2 by applying both fuzzy and non-fuzzy system was plotted in Fig. 14-16, respectively. The proposed work

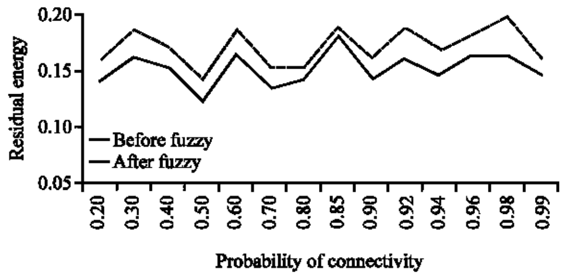

Fig. 15: Residual energy vs. probability of connectivity (150 nodes deployed in the area 90000 m^2)

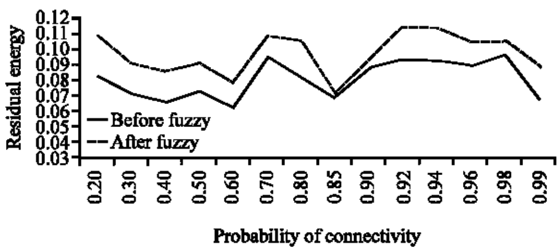

Fig. 16: Residual energy vs. probability of connectivity (200 nodes deployed in the area 160000 m^2)

produces comparatively better results in all the probabilities as shown in. Every node is remain active in non-fuzzy system.

In the proposed fuzzy based system, some fraction of nodes are turned to off and some are pushed towards the sink. The energy consumed by a node turned to off is nil. The energy consumption of the node is directly proportional to the distance. In the case of pushed sensors, its distance towards the sink is reduced because the sensors are pushed towards the sink up to the distance of 0.5 RC. From Fig. 14-16, it is clear that the residual energy is found to be greater in the proposed fuzzy based system in all the cases except for a case 50 nodes deployed in 10000 m^2.

The connectivity requirement will vary based on the underlying application. The proposed fuzzy based system gives a brief layout, so that one can set the communication radius based on the requirement.

Throughput: Throughput is defined as the ratio of total number of packets received to the total number of packets generated. In the proposed fuzzy based system, the number of nodes involved for communication is reduced by removing only the redundant nodes. An extensive care is taken to distribute the sensors evenly throughout the network in the proposed fuzzy based system.

One sink is included in the proposed fuzzy based system and it is wholly responsible for all the data

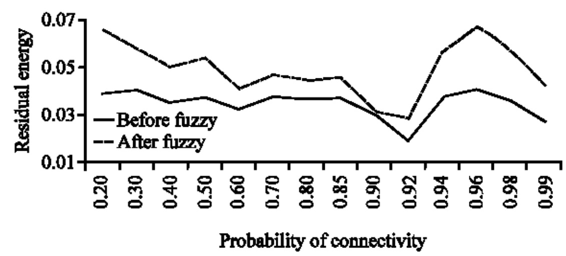

Fig. 17: Residual energy vs. probability of connectivity (250 nodes deployed in the area 250000 m^2)

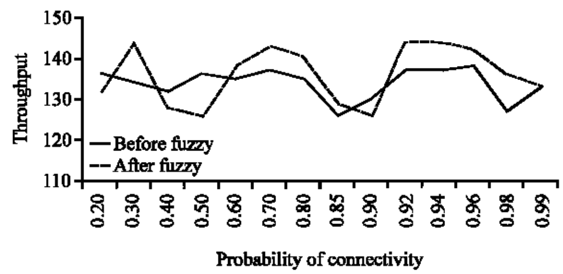

Fig. 18: Throughput vs. probability of connectivity (150 nodes deployed in the area 90000 m^2)

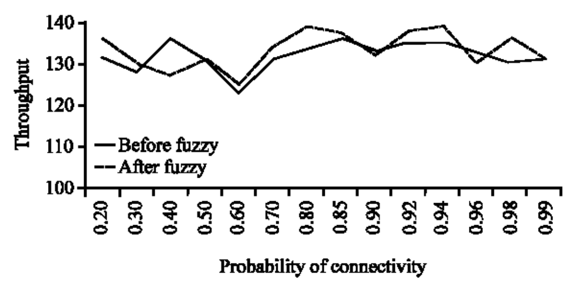

Fig. 19: Throughput vs. probability of connectivity (200 nodes deployed in the area 160000 m^2)

collection. For even distribution, the following constraints are considered. That is, the sensors with more number of neighbors are not allowed both in the near and to the far of the sink position. The number of data processed by the sensors near the sink will be comparatively more by the sensors at the farthest. Always, it is preferable to have moderate number of sensors near the sink to avoid data loss and to balance the overload. The sensor at the farthest will communicate the sink through long distance which will degrade the throughput.

The throughput was calculated for different network parameters and is shown in Fig. 17 and 18. He resultant throughput on deploying 150 nodes in the area 90000 m^2 in different probabilities shown in. Is plotted in Fig. 19 and

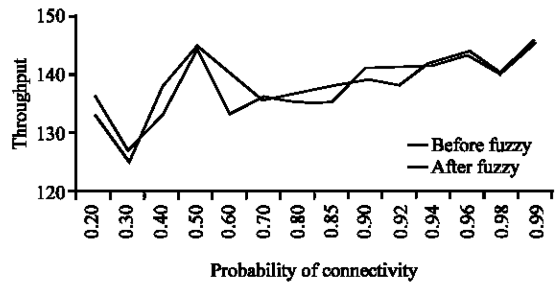

Fig. 20: Throughput vs. probability of connectivity (250 nodes deployed in the area 250000 m^2)

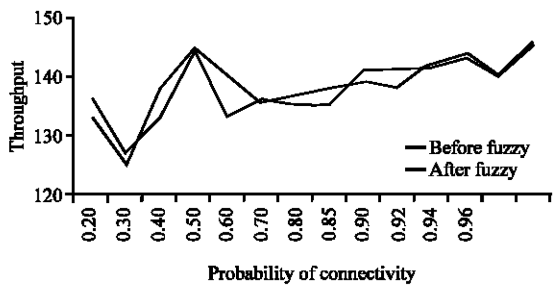

Fig. 21: Throughput vs. probability of connectivity (300 nodes deployed in the area 360000 m^2)

20 by applying both fuzzy and non-fuzzy system. The proposed fuzzy based system results show that the decreased throughput for the probabilities 0.2, 0.4, 0.5 and 0.9 whereas it produces comparatively more throughput for the probabilities 0.3, 0.6, 0.7, 0.8, 0.85, 0.92, 0.94, 0.96 and 0.98. For the probability 0.99, both fuzzy and non-fuzzy systems produce same throughput.

The resultant throughput on deploying 200 nodes in the area 160000 m^2 was represented in Fig. 20 with different probabilities as shown in by applying both fuzzy and non-fuzzy system. The proposed fuzzy based system outperforms the non-fuzzy system with the probabilities 0.4, 0.5, 0.6, 0.8, 0.94, 0.96, 0.98 and 0.99. Also, the proposed fuzzy based system produces the decreased throughput for the probabilities 0.2, 0.3 0.7, 0.90 and 0.92.

The throughput produced by the proposed system on deploying 300 nodes in the area 360000 m^2 was plotted in the Fig. 21 for different probabilities as shown in by applying both fuzzy and non-fuzzy system. The resultant throughput seems to be higher for the probabilities 0.4, 0.5, 0.6, 0.80, 0.85, 0.90, 0.94, 0.96, 0.98 and 0.99 whereas the resultant throughput is found to be lesser for the probabilities 0.2, 0.3, 0.70, 0.92. If the throughput is high, the data loss will be low. So, it is always necessary to have high throughput.

The overall performance of the proposed fuzzy based system gives better results in the large scale network with respect to the small scale network in achieving various aspects like coverage, residual energy and throughput. Even though, the non-fuzzy system produces better results for some of the probabilities but the proposed fuzzy based system outperforms the non-fuzzy system for most of the probabilities. Extensive care must be taken to fine tune the proposed fuzzy based system in order to get better results in all the probabilities so that, it can be applicable for a variety of applications.

CONCLUSION

Wireless sensor network plays a vital role in various areas of applications. Deployment and re-deployment of sensors are unavoidable in real time dense network. There is a tradeoff between the requirement and necessity of redundancy level in the network. In the proposed system, a fuzzy based solution is introduced for avoiding the redundancy and redeploy the sensors on need. There are many network parameters which directly or indirectly influence the resultant redundant effect. Among these, some of the factors are included like connectivity, coverage, distance and density of the network to calculate the degree of redundancy. A fuzzy based decision making system helps to fine tune the system to find the redundant sensors and make optimal decisions either on, off or push action. The simulation results show that the fuzzy based system outperforms in the aspect of residual energy, coverage and throughput. Our future work is focused on fault tolerant system i.e. how effectively an inactive sensor can be used to replace any of the failure nodes in the network by altering the existing topology with minimal changes.

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