Optimising Network Control Traffic in Resource Constrained MANETS

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Optimizing Network Control Traffic in Resource Constrained MANETs

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Abstract- **The exchange of *Network State Beacons* (NSBs) is crucial to monitoring the dynamic state of MANETs like sensor networks. The rate of beacon exchange (F_X) and the network state define both the time and nature of a proactive action to reconfigure the network in order to combat network performance degradation at a time of crisis. It is thus essential to select the F_X within optimized bounds, so that minimal control traffic is incurred due to state maintenance and reconfiguration activities. This paper presents a novel distributed model that selects optimized bounds for F_X selection and adapts dynamically to the load profile of the network for energy efficient monitoring and proactive reconfiguration.**

Keywords- **High Density Ad-hoc Networks, Self Configuration, Distributed Adaptive Optimization, Beacon Exchange Rate**

I. Introduction

Ubiquitous Sensor Networks (USN) comprise hundreds of low-cost *Pervasive Sensor* (PS) nodes with low computation, communication, storage and energy resources. These networks are typically deployed to accomplish highly sophisticated and critical biological, chemical and physical sensing tasks. Such applications impose significant demands upon a network such as; high fault tolerance, longer life, maximum throughput and a self-configuring capabilities. In addition, optimizing energy consumption and bandwidth conservation are crucial for quality-of-service (QoS) provision in ubiquitous computing environments.

To satisfy operational requirements, intermediate nodes called *Parent Nodes* (PN), which have relatively high resources, are used. These nodes are responsible for such tasks as in-network data processing, communication delay minimization and routing of PS nodes data to the Central Commanding Infrastructure (CCI). As these USN building blocks can fail due to unforeseen local or non-local factors, in order to maintain a minimum QoS for a USN, (which in this context is defined as lossless information delivery at minimal control traffic rates), PNs can be dynamically added or removed from the infrastructure. The non-administrated USNs must be self-monitoring and able to take proactive action to mitigate certain malfunctions before they actually occur.

Proactive network monitoring and reconfiguration requires maintaining the network state across the PNs at optimized instants to militate against prospective anomalies. The state profile is maintained by periodic exchanges of NSBs at a particular Beacon *Exchange Rate (F_X)*. The rate of NSBs constitutes the additional load that the network must support in its reconfiguration activities. The load profile of the network is a key determinant of the network performance and typically defines the course of predictable anomalies in the network, such as the loss of connectivity due to energy shortage. Accurate and timely network information, including the estimated lifespan of key nodes and network load profile enables an effective and proactive strategy to be formulated to alleviate potential network impairments. These operational requirements demand the analytical selection and updation of F_X in accordance with the load dynamicity in the network. This leads to the definition of optimal bounds within which this F_X must lie. Also the selection of F_X within the bounds must fluctuate minimally so that the control overhead on the network for exchanging reconfiguration and/or network state information is minimized. This process of controlling F_X within optimal bounds and within a *Region of Existence* (ROE) is non trivial to maximizing network throughput while concomitantly minimizing the risk of information loss due to node failures.

Previous work on self-configuring protocols has not focused upon investigating the role the *beacon exchange rate* plays in maintaining a QoS for the network. Gupta [1] and Chiasserini [2] have focused on energy-efficient, hierarchical modelling of sensor networks through dynamic configuration of the tree nodes. The success of their dynamic tree models is based on a problematic assumption that sensor nodes are able to connect to many PNs simultaneously. Cerpa in [3] emphasized the need for a high degree of synchronization between network components in order to correctly reconfigure. Policy-based and self-managing systems have been also considered, but these impose a high computational and storage requirement on individual sensing units.

This paper presents novel improvements to a proactive self-configuration model [4, 5] by analytically defining the optimal bounds on F_X and establishing its *ROE* while significantly reducing overhead traffic and maintaining a guaranteed QoS. The research develops a distributed adaptive model to dynamically update the rate in response to network load profile changes.

The remainder of the paper is organised as follows; Section II briefs the underlying USN design and self configuration model, while Section III details the distributed load-adaptive F_X selection model. Simulation results focusing upon the maintenance of QoS and reliability of configuration model are given in Section IV and conclusions are presented in Section V.

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II. Sensor Network Design & Self Configuration

A. Network Design

The sensor network design approach described in [6] is based upon the optimal selection of PN density and location in a virtual hexagonal topology structured in autonomous clusters with each cluster headed by a PN. This approach is adopted to achieve the best QoS by ensuring the availability of PN to a maximum number of PS nodes, while minimizing Grey Region (GR) areas (to reduce many-hop routing) and minimizing confusion/conflict zones.

B. Self Configuration Core Protocol

The network design defines the initial configuration of the sensor network for best QoS with the communication and connectivity model for the PN and PS nodes described in [5]. In the steady state network operation, the model can handle a number of irregularities including: a) increased traffic load leading to congestion and packet losses causing loss of information, b) decreased energy resources increasing the risk of PN failure, c) sudden failure of a PN due to local or non-local disasters and d) addition of new PNs.

To address these various scenarios, a *Self-Configuration Protocol* is employed, with the key element being the continual geographical monitoring of the network state. The protocol focuses on employing *Associate Parent Nodes* (APNs) from within the sensor nodes that work as adhoc routing devices and point of access for the devices in a failed cluster [5].

Network State Management: Network state profile can be maintained in both distributed and centralized manners. For this purpose, NSBs are exchanged amongst the PNs throughout the network at the F_X rate. The exchange of NSBs between neighbouring PNs defines the local state of the network at each cluster in terms of network load, remaining energy, remaining life of the PN and the PN availability. The rate of exchange and method of propagation of NSBs are the key factors in defining the nature, time and effectiveness of any proactive action. The following section discusses these two factors in presenting a model that achieves superior performance in terms of more effective energy consumption and reliable data transmission.

III. Beacon Propagation and Exchange Rate

A. Beacon Propagation

NSBs are exchanged by the neighbouring PNs in the whole network to maintain the state. As stated earlier, network state can be maintained either centrally or in a distributed fashion. For central network monitoring, the NSBs from each cluster head must be propagated to the CCI and the rate of exchange should also be global and communicated to each cluster head. Fig. 1A illustrates the centralized propagation scheme. For connected networks, it is possible to declare a PN from within the network as a head node to minimize the long range communication with CCI to one PN only to maintain the network state centrally. This head node also works as a gateway of the PN network to external world. The head PN periodically sends aggregated state information to CCI and takes input from the CCI for what F_X should be maintained and which reconfiguration is to be undertaken. This information is routed throughout the network by adopting one of geography-based ad hoc routing strategies. For this purpose, the GEAR [7] protocol is employed which is a recursive data dissemination protocol for wireless sensor networks. GEAR is selected for F_X propagation because of its proven performance in highly dense wireless sensor networks, while consuming minimum energy.

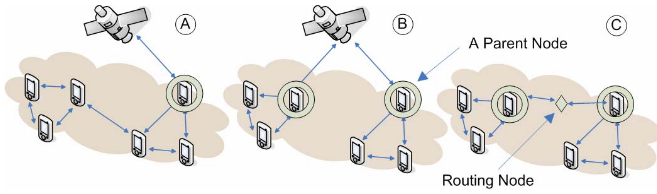

Fig. 1. A: For connected networks, in-network routing (GEAR) is employed for beacon and F_E propagation with one PN acting as gateway to external world, B: Partially connected networks employ Hybrid interconnectivity for maintaining the state and F_E centrally, C: Decentralized architecture lets clusters maintain the state and F_E locally

Fig. 1B illustrates partially connected and a centralized network state management scheme in which a *hybrid* interconnectivity approach is employed, with each cluster headed by a PN which in turn connects to the CCI for sending NSBs and receiving F_X updates.

However, the inherent decentralized structure and high density of USNs reduces the importance of CCI for steady state operation and reconfiguration of the network. Fig. 1C illustrates decentralized clusters, with each cluster headed by a PN and each cluster maintains its local state and own F_X tuned to the requirements of that cluster. This distributed state management scheme prevents the need to have inter-cluster communication for NSB propagation, except appointing APNs [5]. These APNs establish multi-hop linking between clusters, thereby forming a connected network within a decentralized one. Under steady state situations, these links remain inactive and clusters keep their operations isolated from each others, except mobile source localization and surrogate tracking. This idea of cluster activity optimization in isolation is based on decentralized and self configuring pheromone based communication in ants and termites while they locate food sources or build-up meters high mounds [8].

Since the cluster heads define the backbone of the network and their life is crucial to the overall life of the network, in this work, the role of cluster head is randomly rotated among all cluster nodes to ensure the network energy resources drain evenly thereby protecting the network from experiencing non-uniform impairments. To assign nodes to the cluster heads in an energy efficient way, the usual minimum transmission power criterion is not employed because of its excessive communication and processing overheads. Instead, the node assignment is optimized to maximize the lifetime of the entire network [2], which is given by:

$$L_s = \sum_{i \in S_c} L_i \tag{1}$$

where L_s is the network life time for a given energy for all clusters; S_c is the set of cluster heads while L_i is the lifetime of a single cluster head, defined by:-

$$L_i = E_i[\alpha c_i + f(n_i)]^{-1} \quad (2)$$

where $E_i\psi$ is the initial energy available at cluster head $i\psi$ and the two denominator terms respectively represent the power consumption contributions due to the output transmit power and cluster-head transmitting/receiving activity.

B. Bounds on Beacon Exchange Rate

The rate of beacon exchange is measured in terms of beacon exchange interval (F_E). We have investigated the impacts of different F_E selection methods on the network performance and state management. These include a) Random Interval (RF_E), b) Load Based Centralized Interval (CF_E) and c) Load Based Distributed Interval (DF_E).

The reason for employing random exchange rate is to find out the core effects of employing beacon exchange on self configuration in general and proactivity in particular. However, random beacon exchange rate [4] does not reflect the true state of the network. Instead, the selection of the exchange rate based on the load profiles of the clusters provides a better picture. This profile can be established either centrally or in a distributed fashion. The rationale is to keep tuning the exchange rate throughout the network with respect to the level of network activity. If the network undergoes a high load scenario, the energy profiles of PNs will degrade quickly. In this situation, the network state is highly dynamic and beacons must be exchanged more frequently, but at a rate that consumes the least additional energy by optimally adapting to new load profile of the network and maintaining the actual state of the network across all clusters.

The amount of deviation in load defines the dynamical behaviour of the network. This amount of dynamicity defines the rate with which the NSBs must be exchanged for state maintenance. For this purpose, each cluster head maintains some statistics that help in calculating the rate of switching between various loads ($\Delta\sigma^2 / \Delta t$). These statistics include:

U_t: Load on the cluster at time 't'

n_t: Number of Load readings till time 't'

$\sum U_t = U_t + \sum U_{t-1}$ and $\sum U^2{}_t = U^2{}_t + \sum U^2{}_{t-1}$

Given these values, rate of dynamicity in load is calculated by the rate of change of variance in the load (ω_t), given by:

$$\sigma_t^2 = \frac{n_t \sum U_t^2 - (\sum U_t)^2}{n_t(n_t - 1)}$$

$$\omega_t = \frac{\sigma_{t_f}^2 - \sigma_{t_i}^2}{t_f - t_i} = \frac{\Delta\sigma_{t_f}^2}{\Delta t_f} \quad (3)$$

In calculating the rate, two bounds on F_E need to be set, the upper interval bound ($F_{E\max}$) being the rate with which the NSBs must be exchanged to maintain the network state even in the case of significantly lower network load. The lower bound ($F_{E\min}$) limits the maximum exchange rate, exceeding which places extra load on the network due to very frequent NSB exchanges and, actually may result in redundant NSBs being observed and propagated [4].

TABLE I – Beacon Exchange Upper Bound Selection and Updation

a. Set $F_{E\max} = 1$
b. Calculate ω_t
c. Do While ω_t □ 0
d. $F_{E\max} = 2 * F_{E\max}$
e. Calculate ω_t
f. End While
g. Do While $\omega_t >> 0$
h. $F_{E\max} = F_{E\max} - 1$
i. Calculate ω_t
j. End While

The upper bound ($F_{E\max}$) is defined by the rate of change of variance of load. Equation (3) suggests that a higher ω_t indicates non-steady network state which changes more often in a given time interval (t_f , t_i). This situation requires the beacon exchange rate to be increased proportional to the rate of load variance (ω_t). On the other hand, if the network is in strict ideal state where ω_t □ 0, it operates in predictable load range and therefore beacon exchange rate for state maintenance should be significantly reduced. This implies that the upper bound ($F_{E\max}$) must be selected and modified according to the rate of change of load variance ($\Delta\sigma^2 / \Delta t$). Table I details the complete procedure of establishing $F_{E\max}$.

Proposition I: The upper bound $F_{E\max}$ selected proportional to ω_t represents an optimal upper bound that generates minimum redundant network state information and provides closest network picture at any given instant.

Proof: Let T_R be the optimal upper bound for F_E that satisfies both conditions mentioned above. The upper bound ($F_{E\max}$) defined by algorithm in Table I reveals that as long as the upper bound $F_{E\max}$ is less than T_R, the state of the network is observed at higher resolution than required and, therefore, will be available in any critical situation. However, if $F_{E\max} << T_R$, then redundant NSBs could be propagated, resulting in exceedingly overhead proactivity actions. On the other hand, if $F_{E\max}$ gets greater than the T_R, the NSB exchange will be less frequent than the required and so there is probability that at times the network will be *under-stated*, a state where actual picture of current network state is not available. In order to avoid these two extreme conditions of *redundancy* and *under-stateness*, it is required to optimize $F_{E\max}$. Consider the following relationship:

$$d = T_R - F_{E\max}$$

The optimal upper bound of F_E should be as close to T_R as possible such that $F_{E\max}$ minimizes $|d|$. This relationship forms a *Region of Existence* (ROE) which is illustrated in Fig. 2 after simulated investigation of a number of networks of various dimensions, densities and traffic patterns. ROE defines the optimal range for the selection of upper bound that would keep network state safely normal thereby avoiding

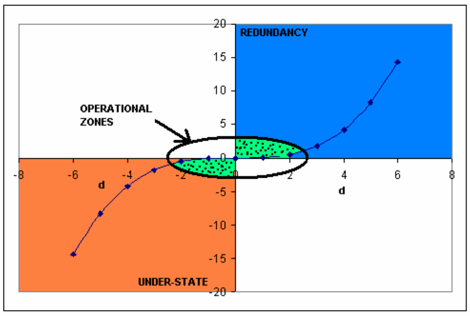

Fig. 2. Optimizing the upper bound of F_E. Dotted areas show the acceptable operational regions within which the two extreme conditions are safely avoided. Upper bound $F_{E\max}$ must be selected to keep d in these regions

the two extreme conditions. The algorithm presented in Table I tunes upper bound in such a way that:

a. Initially, $F_{E\max}$ is kept very low such that it tracks even the minor fluctuations in the load. This is followed by exponential increase in the upper bound to a point where ω_t becomes significantly high. This makes $d << 0$ and assures that the information retrieved is not only non-redundant but also suffers from some understate situation.
b. In the second step, the observed rate of change of network load variance is taken back close to zero. This means that a sufficiently small interval is selected such that no the information loss is minimum and network state is tracked optimally.

These two steps satisfy the conditions for optimality. ■

The lower bound ($F_{E\min}$) on exchange interval is determined by considering the total load on the network as:

$$\eta = U_{Total} + \left[\frac{T_f - T_i}{F_{E\min}}\right]\bar{U} \quad \text{where} \quad U_{Total} = \int_{t=T_i}^{T_f} \sum_{i=0}^{F_n} U_{it} \qquad (4)$$

where U_{Total} in above equation gives total load on the network within the given time interval $\{T_i, T_f\}$. Where U_{it} is the load on PN "i" at time "t", $\bar{U}$ is the extra load caused by a each state management operation, F_n is number of clusters and η is the total load on the network, including the load caused by proactivity, at time T_f. The second term in (4) is the load caused in this interval by proactive activities. Given the extra load policy factor k, that defines the amount of extra load that the network can sustain with, η defines the lower bound of F_E by satisfying:

$$\eta \le \left(1 + \frac{k}{100}\right) U_{Total} \qquad (5)$$

i.e. $F_{E\min}$ must keep η within the allowed extra $k\%$ load.

It is observed that $F_{E\max}$ defines the lower limit on the extra load allowed (k), since the minimum amount of control traffic generated by state maintenance operations, while exchanging NSBs after every $F_{E\max}$ units of time, is mandatory. It means that k_{min} is dependant on $F_{E\max}$. To numerically define this relationship, the extra load (W) introduced by optimal $F_{E\max}$ is given by:

$$W = \left[\frac{T_f - T_i}{F_{E\max}}\right]\bar{U} = \left[\frac{T_f - T_i}{T_R}\right]\bar{U} \quad for \quad F_{E\max} = T_R \qquad (6)$$

In order to conform to the design-policy:

$$W \le 0.01k * U_{Total} \qquad (7)$$

$$\Rightarrow \; k \ge 0.01W * (U_{Total})^{-1} \; \Rightarrow \; k_{\min} = 0.01W * (U_{Total})^{-1} \qquad (8)$$

Equation (8) defines the minimum value of k that should be used while allocating the allowed extra load overhead. This relationship between k and $F_{E\max}$ reveals that $F_{E\min}$ is implicitly defined, as soon as $F_{E\max}$ is defined and is given by:

$$F_{E\min} = \frac{(\bar{U})(T_f - T_i)}{0.01(U_{Total})(k_{\min})} \qquad (9)$$

A further increase in value of k increases the amount of extra load allowed which decreases $F_{E\min}$ thereby allowing the network to be monitored at a higher rate. However, the maximum value of k is not linearly dependant on $F_{E\max}$; rather it is defined by the required life time of the network. Recall equation (2) that defines the lifetime of a single cluster head, after incorporating the proactive activities, the new life time is given by:

$$L_i = E_i(\alpha c_i + f(n_i) + p(W_i))^{-1} \qquad (10)$$

where the added term $p(W_i)$ represents the contribution to power consumption due to extra load introduced by cluster head i for proactive activities. Now, from (8), if:

$$W = 0.01K_{max} * U_{Total} \qquad (11)$$

then $k_{\max}$ should be selected in such a way so that: $L_s \ge L_{REQ}$ where L_{REQ} is the required life of the network and is decided by the network architect.

C. Beacon Exchange Rate Selection and Updation

Having defined the boundaries on exchange interval, F_E is initially selected ($F_{E(t)}$ for t = 0) to be equal to the upper bound ($F_{E\max}$) and is updated dynamically as according to the changes in the load profile of the network. This rate is then periodically updated to $F_{E(t+1)}$ using the following linear stochastic feed forward process:

$$F_{E(t+1)} = F_{E(t)}(1 + 0.01\lambda) \qquad (12)$$

where λ is the process that updates the current exchange rate depending upon the change in the load profile of the network. It is given by:

$$\lambda = 1 - \left[\frac{U_{Total(t)}}{U_{Total(t-1)}} - 1\right]^v \qquad (13)$$

v defines a series of curves that plot changes in the F_E for unit changes in load, two examples of which are shown in Fig. 3, where the Load Change Ratio (LCR) is the ratio of the current load to the previous load. For v = 1, the plot is a straight line which induces an inverse change in λ as the load changes, while for higher v values, the curve takes on the shape of a logistic change. This logistic change resulted in better network performance which was due to a lower synchronization requirement amongst the PNs supported by less frequent changes in λ. This is clear from Fig. 3, where for v = 3 the only notable change in λ occurs when the average load deviates significantly from the unity (i.e. LCR=1 so the

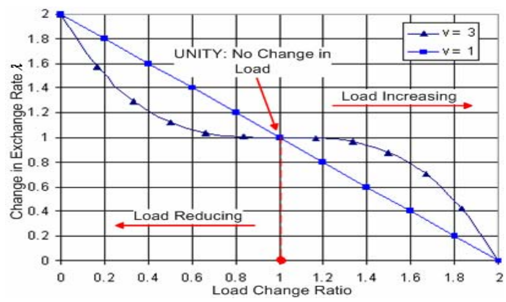

Fig. 3. Beacon Exchange Rate change induction curves defined by 'v'

current and previous loads are the same). An important design aspect here is that for a particular load, this logistic change in λ only supports load changes (increasing or decreasing) by a factor of two. For changes beyond this factor, the curve becomes a straight line as for v=1 and changes in λ are induced equivalent to the changes in load, until the logistic curve is again applied at some point on the network load prevailing at that time.

IV. SIMULATIONS

We conducted extensive simulation experiments to evaluate the performance of the proposed model for F_E selection, which was implemented in both a centralized and distributed manner for different load profiles and node densities. While developing the simulation test bed, the guidelines by [9-11] were considered for testing the validity of conceptual model of the network, validating the reality-check of underlying assumptions / limitations about network's internal mechanisms and calculating the confidence intervals for 95% confidence level.

Unless otherwise specified, we assumed a variety of systems running with 200 to 500 sensor nodes and 30 to 50 cluster heads, to simulate ad hoc networks with varying levels of cluster cardinalities. These nodes were randomly dispersed into an open irregular terrain with approximately 25000m² dimensions. The distance between nodes was used to account for the required transmission power level among them. We vary the cluster radius from 50 to 450 to study how the model works with low to high coverage ranges. The results shown are the averages of 80 sequential experiments conducted to control the errors of final results and establish 95% confidence level. Each experiment uses a different randomly generated topology for sensor nodes, while the cluster heads are deployed according to the design model given by Iqbal et al [12]. The locations of APNs vary depending upon the combined topological connectivity of sensor nodes and CHs, and are determined by employing LACON protocol [13]. Each sensor node is assigned identical randomly-generated residual energy level between 0 and 2 Joules (J) and each CH is assigned an initial energy between 15 and 20 Joules.

Control packet lengths are fixed to 2 Kbits [14]. It is assumed that the channel is collision free and a node sensing a target produces data packets at a rate that is tuned to generate one of the various network-wide load profiles shown later. We assume that each cluster head can handle at most 15 nodes in its cluster in terms of resource allocation. Each

TABLE II. SIMULATION ENVIRONMENT PARAMETERS

Attribute	Value			
Area under Surveillance	Open irregular terrains of dimensions 25000m²			
Deployment Topology	Random for both PS & PN nodes			
CH Comm. Range (m)	50-450			
Density of PS nodes	200-500			
Density of PN nodes	30-50			
F_E Implementation	No, Centralized, Distributed			
Sampling Rate	5 Sec			
Control Packet Size	2 Kbits			
Network Activity Time (mins)	80 Sequential experiments, 900-1800 seconds time for each run			
Power Consumption (mW)	Tx	Rx	Idle	Sleep
	14.88	12.50	12.36	0.016

simulation ran from 900 to 1800 seconds, and the network was *sampled* every 5 seconds. Table IV summarizes the simulation environment parameters. Packet Loss, Network Integrity and Energy Consumption were used as *QoS* performance metrics. These statistics provided basis for evaluating the performance of HUSEC and are defined below.

- *Packet Loss*– The difference in the total number of data packets sent by the sensors and number of packets that could reach any CH. This is a measure of network reliability in case of unprecedented backbone node losses.
- *Network Integrity*– The percentage of sensors which have access to the backbone through at most 3 hops. The limitation on number of hops is due to underlying self configuration protocol LACON [13]. This statistic measures the amount of robustness incorporated in the network by our model due to exchange of F_E suited to the network load state. Robustness is defined here as the amount of connectivity support made available to sensor nodes, to keep the traffic intact, in an event of large number of CH losses.
- *Energy Consumption*– The amount of extra energy consumed for beacon exchange over the life of the network. This statistic is used to analyse the extra energy consumed by the model for maintaining an effective network state. Since the model utilizes some control traffic (NSB exchange) in order to improve network performance (network integrity, throughput), it is important to analyse the cost of this improvement in terms of energy.

The following subsections analyse each of these performance metrics in detail.

A. Packet Loss

Fig. 4 illustrates packet losses due to randomly failing nodes in the network for the CF_E, DF_E and no-F_E strategy. Overall, a saving of up to 65% in packet loss due to failing nodes was achieved when the beacon exchange strategy was employed for network state management. The distributed version of the model performed better than the centralized one, resulting in further 5-10% savings in packet loss. This was because of the high degree of synchronization between the load profile of the clusters and F_E in the case of DF_E. The centralized control lags behind in performance due to global communication delays and also due to unnecessary extra load (for proactivity)

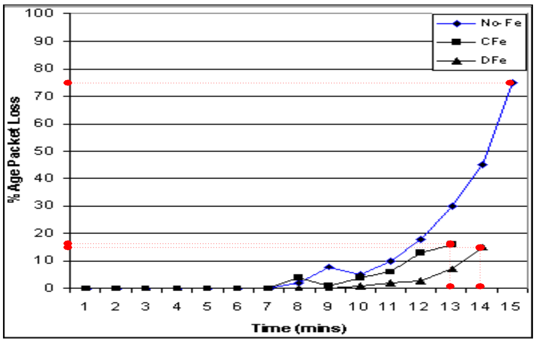

Fig. 4 Comparison of Average Packet Loss for CF_E, DF_E and no Beacon Exchange

being imposed on various PNs that render them low in energy resources much earlier than in the distributed model. This early failure of PNs is also illustrated in graph where network in centralized mode lost its power one minute earlier than in the distributed mode. Moreover, the smoother transition of the DF_E curve illustrates better proactive action of the self configuration model protects the network from unprecedented losses and arranges in advance, solutions to the potential malfunctions. The graphs also reveal the important impact of F_E on the life time of the network, with network life reduced in both cases (CF_E and DF_E) compared to when there is no F_E applied. The key to emphasise is the trade-off between lifetime and the reliability of data transmission. In the case of DFE and CFE, network life is reduced from 15 to 14 and 13 minutes respectively, but the confidence level of data transmission is enhanced by up to 65%. The confidence intervals for the observed savings in packet loss were calculated for 95% confidence level. For CF_E, the intervals were ±4%, while for DF_E, these were ±8.7%.

B. *Network Integrity*

Fig. 5 shows the effects of PN failure on overall connectivity of PS nodes in the network. PNs were randomly triggered to fail and the effect on sensor-parent connectivity analyzed for both situations when self-configuration was active with DF_E and CF_E and when it was inactive. The graph confirms that the network captures approximately 70% of network traffic through proactively reconfiguring connections via routing nodes, even when half the PNs failed. An important point to note is the slight drop in performance of DF_E hen more than two thirds of the nodes have failed. While statistically insignificant, this effect was noted in most of the experiments to be because of fewer PNs being available to form multi-hop

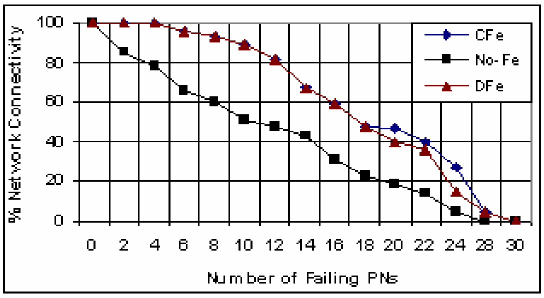

Fig. 5 Effect of Parent Node Failure on Network Integrity for DF_E and CF_E

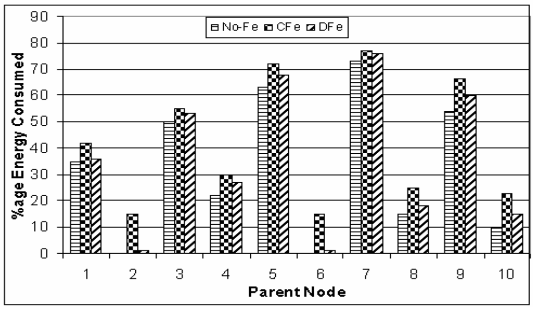

Fig. 6 Comparison of Energy Consumption at various PNs for CF_E, DF_E and no Beacon Exchange

connections to outlying clusters via APNs. This hiatus renders the model incapable of securing help from other parts of the network which are still operative. Beyond this point, both DF_E and CF_E maintain similar levels of connectivity across sensing devices.

The confidence intervals for identifying the precision of the results were calculated for 95% confidence level. For both CF_E and DF_E, the intervals were ±6%.

C. *Energy Consumption*

To investigate the superior performance of DF_E in terms of savings in packet loss over CF_E, an analysis of the energy consumption was done for selected PN nodes. The nodes which made key difference in defining the packet savings due to their proximity were selected. Fig. 6 shows the energy consumed by ten PNs in DF_E, CF_E and no-F_E situations. It is clear that as CF_E maintains a global exchange rate, it consumes more energy due to long range communications and extensive in-network routing. In this way, it even keeps those PNs busy in sending NSBs which are inactive, rendering their energy to be consumed more as confirmed from the energy consumption profile of PN 2 and 6. On the other side, since the exchange rate decision is made locally in a cluster in case of DF_E, the PNs are kept alive proportional to the load on the cluster. This helps in utilizing PN energy optimally for producing throughput and least energy is consumed for self configuration activities.

V. CONCLUSIONS

This paper has presented a new *beacon exchange rate* selection and tuning technique for centralized and distributed load based methods of beacon propagation. Both analytical and simulation results have shown that optimising the exchange rate provided a significant performance improvement over proactive self configuration protocols in handling network malfunctions, including node failure and overload. Numerical bounds on the maximum and minimum values of the exchange rate have been developed and an operational zone established to minimise the risk of reaching either the *redundant* or *understate* situations. The results also confirmed the model's stability in terms of inducing logistic changes in F_E for a normal network load profile which adapts to load changes in such a way that network synchronization requests are minimized. The proposed model was found to be very robust with more than 70% of component devices observed connected through development of multi-hop routes in a sensor network.

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