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# Distributed and Load-Adaptive Self Configuration in Sensor Networks

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**Abstract-** Proactive self-configuration is crucial for MANETs such as sensor networks, as these are often deployed in hostile environments and are ad hoc in nature. The dynamic architecture of the network is monitored by exchanging so-called *Network State Beacons* (NSBs) between key network nodes. The *Beacon Exchange Rate* and the network state define both the time and nature of a proactive action to combat network performance degradation at a time of crisis. It is thus essential to optimize these parameters for the dynamic load profile of the network. This paper presents a novel distributed adaptive optimization *Beacon Exchange* selection model which considers distributed network load for energy efficient monitoring and proactive reconfiguration of the network. The results show an improvement of 70% in throughput, while maintaining a guaranteed quality-of-service for a small control-traffic overhead.

**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 set *Beacon Exchange Rate* ( $F_E$ ). 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. It is therefore important to attempt to optimize these factors by considering the current network load and maximise 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 [6,7] by significantly reducing overhead traffic while maintaining a guaranteed QoS. The research establishes bounds for selecting  $F_E$  and 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 explores the underlying USN design and self configuration model, while Section III details the distributed load-adaptive  $F_E$  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.

## II. SENSOR NETWORK DESIGN & SELF CONFIGURATION

### A. Network Design

The sensor network design approach described in [8] 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 [7]. In

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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 [7], with the key element being the continual local geographically monitoring of the network state.

**Network State Management:** In order to monitor the network for impairments and malfunctions, it is crucial to maintain the state of the network. This 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  $F_E$  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.

## II. 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  $F_E$  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 [10] protocol is employed which is a recursive data dissemination protocol for wireless sensor networks. GEAR is selected for  $F_E$  propagation because of its proven performance in highly dense wireless sensor networks, while consuming minimum energy.

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  $F_E$  updates.

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  $F_E$  tuned to the requirements of that cluster. Subsection III-B details  $F_E$

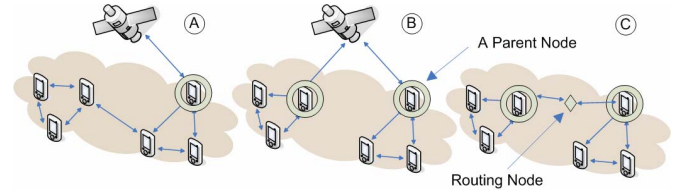


Fig. 1. A: For connected networks, in-network routing (GEAR) is employed for beacon and  $F_E$  propagation with one PN acting as gateway to external world, B: Partially connected networks employ Hybrid interconnectivity for maintaining the state and  $F_E$  centrally, C: Decentralized architecture lets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

selection and updating methodology. This distributed state management scheme prevents the need to have inter-cluster communication for NSB propagation, except appointing Associate Parent Nodes (APNs) [7]. These APNs are routing nodes for 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 mounds high mounds [11]. Simulations in Section IV show the comparative performance of the different propagation techniques discussed above in terms of their impact on network life and data transmission reliability.

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:

$$L_s = \sum_{i \in S_c} L_i \quad (1)$$

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

### B. Beacon Exchange Rate ( $F_E$ )

The random beacon exchange rate [6] does not reflect the true state of the network. 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.

In calculating the rate  $F_E$  two bounds need to be set, the lower being defined by the minimum rate with which the NSBs must be exchanged to maintain the network state even in the case of significantly lower network load. The upper bound limits the maximum value of  $F_E$ , 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 [6]. The total load on the network for higher bound of  $F_E$  is:

$$\eta = U_{Total} + \left[ \frac{T_f - T_i}{F_{E_{max}}} \right] \bar{U} \quad \text{where} \quad U_{Total} = \int_{t=T_i}^{T_f} \sum_{i=0}^{F_n} U_{it} \quad (3)$$

where  $U_{Total}$  is the total load on the network within a given time interval  $\{T_i, T_f\}$ ;  $U_{it}$  is the load on PN  $i$  at time  $t$ ,  $\bar{U}$  is the extra load caused by one proactivity,  $F_n$  is number of clusters and  $\eta$  is the total load on the network, including the load caused by proactivity, at time  $T_f$ . The second term in (3) is the load caused in this interval by proactive activities. Given the extra load ( $U_x$ ) policy factor  $k$ ,  $\eta$  defines the upper bound of  $F_E$  satisfying:-

$$\eta \leq \left(1 + \frac{k}{100}\right) U_{Total} \quad (4)$$

i.e.  $F_{E_{max}}$  must maintain  $\eta$  within the allowed extra  $k\%$  load.

The relationship between the lower bound ( $F_{E_{min}}$ ) and minimum required update resolution ( $T_R$ ) is given by:

$$F_{E_{min}} \leq T_R \quad (5)$$

However, if  $F_{E_{min}} \ll T_R$ , then redundant NSBs may be propagated, resulting in significant overhead proactivity actions. Conversely, if  $F_{E_{min}}$  is greater than  $T_R$ , the NSB propagation will be less frequent than required so there is a probability that at times the network will be *under-stated*, a condition where the actual picture of current network state is not available. To avoid these two extremes of *redundancy* and *under-stateness*,  $F_{E_{min}}$  needs to be optimized. Consider the following relationship:

$$d = T_R - F_{E_{min}} \quad (6)$$

The optimal lower bound of  $F_E$  must be as close to  $T_R$  as possible so it minimizes the lower bound optimization factor  $|d|$ . This operational zone describes the optimal range for the selection of lower bound that would keep network state safely normal thereby avoiding the two extreme conditions. The relationship between the network state ( $\delta$ ) and lower bound optimization factor ( $d$ ) is given by:

$$\delta \approx d^3 (p)^{-1} \quad (7)$$

where  $p$  is a tuning factor, whose value depends upon the resolution of updating ( $T_R$ ). The operational zone is defined by:

$$-2d \leq \delta \leq 2d \quad (8)$$

Fixing the upper and lower bounds of  $F_E$  is greatly influenced by two design parameters, namely the extra allowable network load  $U_x$  and the network state update resolution  $T_R$ , which are conditionally dependant on each other. This dependency states that for a particular  $U_x$  there is a minimum  $T_R$ , and vice versa, beyond which the update resolution starts placing an additional load on the network than that permitted. To numerically define

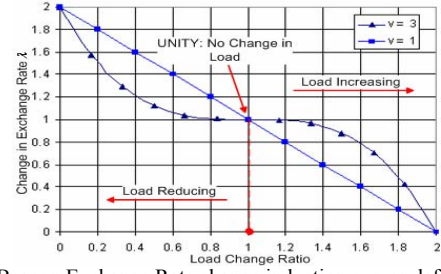


Fig. 2. Beacon Exchange Rate change induction curves defined by  $v$  this relationship, the extra load  $W$  introduced by  $F_{E_{min}}$  is given by:

$$W = \left[ \frac{T_f - T_i}{F_{E_{min}}} \right] \bar{U} = \left[ \frac{T_f - T_i}{T_R} \right] \bar{U} \quad \text{for} \quad F_{E_{min}} = T_R \quad (9)$$

In order to conform to the design-policy:

$$W \leq .01k * U_{Total} \quad (10)$$

$$\Rightarrow k \geq .01W * (U_{Total})^{-1} \Rightarrow k_{min} = .01W * (U_{Total})^{-1} \quad (11)$$

Equation (11) defines the minimum value of  $k$  that can be used while allocating the extra load for a particular update resolution  $T_R$ . Conversely the maximum value of  $k$  is not linearly dependant on the update resolution, but rather it is defined by the required lifetime of the network. From (2), the new lifetime of a single cluster head, after incorporating proactive activities is given by:

$$L_i = E_i(\alpha c_i + f(n_i) + p(W_i))^{-1} \quad (12)$$

where the term  $p(W_i)$  represents the contribution to power consumption due to extra load introduced by cluster head  $i$  for proactive activities. From (10), if:

$$W = .01K_{max} * U_{Total} \quad (13)$$

then  $k_{max}$  should be selected so that  $L_s \geq L_{REQ}$  with  $L_{REQ}$  as the required life of the network chosen by the network designer.

Having defined the exchange rate bounds,  $F_E$  is initially selected ( $F_{E(t)}$  for  $t = 0$ ) to be equal to the lower bound ( $F_{E_{min}}$ ) and is updated dynamically 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 feedforward process:

$$F_{E(t+1)} = F_{E(t)}(1 + .01\lambda) \quad (14)$$

where  $\lambda$  is the parameter used to update the current exchange rate depending upon the change in load profile of the network, which is given by:

$$\lambda = 1 - \left[ \frac{U_{Total(t)}}{U_{Total(t-1)}} - 1 \right]^v \quad (15)$$

$v$  defines a series of curves that plot changes in  $F_E$  for unit changes in load, two examples of which are shown in Fig. 2, where the *Load Change Ratio* (LCR) is the ratio of the current load to the previous load. For  $v=1$ , the plot is linear which induces an inverse change in  $\lambda$  as the load changes, while for higher  $v$  values, the curve takes on the shape of a logistic change, which leads to better network performance due to a lower synchronization requirement amongst the PNs supported by less frequent changes in  $\lambda$ . This is clear from Fig. 2, where for  $v=3$  the only notable change in  $\lambda$  occurs when the average load deviates significantly from *unity*, that is when LCR=1 so



the current and previous loads are the same. An important design aspect is that for a particular load, the logistic change in  $\lambda$  only supports load changes by a factor of two. For other changes, the curve becomes linear and changes in  $\lambda$  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.

### C. Implementation Method

$F_E$  selection and tuning model defined by the boundary equations (3)–(6) and update equations (14) and (15) is implemented in both centralized (Fig. 1A, 1B) and distributed (Fig. 1C) fashion. In case of centralized control, the CCI governs the calculation of  $F_E$  which is then communicated to the cluster heads for implementation. Also the cluster heads send the updates on network state to CCI and, in response, receive necessary reconfiguration instructions. The load parameter in the equations would refer to the total load on the network while the life would be defined as the sum of the lives of all cluster heads. When the model is decentralized, the clusters behave as autonomous network regions and calculation of  $F_E$  is devolved at cluster head level. Also the state of the network is managed locally and communicated to other clusters only in the case of anomalies through routing nodes. This methodology makes the structure self-sufficient in its operation not depending upon external communication infrastructures (such as CCI) for  $F_E$  tuning and reconfiguration. Simulation results in the following section further quantify these arguments and provide a performance comparison of the model.

## III. SIMULATIONS

Simulations were carried out to evaluate the performance of the network with  $F_E$  selection and communication model implemented in both centralized ( $CF_E$ ) and distributed ( $DF_E$ ) ways for different load profiles and PN malfunctions. Table I details the complete simulation environment parameters. Packet Loss, Overhead Control Traffic, Network Integrity and Energy Consumption were used as  $QoS$  performance metrics.

### A. Packet Loss

Fig. 3 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) 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

TABLE I. SIMULATION ENVIRONMENT PARAMETERS

Attribute	Value			
Area under Surveillance	Open irregular Terrains of 25000m <sup>2</sup> dimensions			
Deployment Topology	Random for both PS & PN nodes			
PS Comm. Range	3m			
PN Comm. Range	3m-13m			
Density of PS nodes	125-143 Randomly Deployed			
Density of PN nodes	25-30			
Mobility	Stationary PNs & Mobile PS nodes			
$F_E$ Implementation	Centralized, Distributed			
QoS Metrics	Packet Loss, Overhead Control Traffic, Network Integrity, Energy Consumption			
Control Packet Size	500bytes			
Network Activity Time	15 min			
Power Consumption (mW)	Tx	Rx	Idle	Sleep
	14.88	12.50	12.36	0.016

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  $DF_E$  and  $CF_E$ , 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%.

### B. Network Integrity

Fig. 4 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  $DF_E$  when more than two thirds of the nodes have failed. This is because of fewer PNs being available to form multi-hop 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.

### C. Control Overhead

To quantify the impact of the  $\lambda$  curves (Section III-B) on the overhead control traffic required for maintaining the network state across all PNs, the network was tested under various load profiles, with Fig. 5A showing increasing, normal and random load profiles applied on the network. From earlier theory, the logistic change in  $F_E$  was developed to support only network load changes by a factor of two. It was anticipated that for

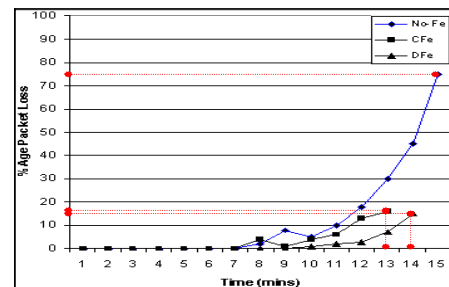


Fig. 3 Comparison of Average Packet Loss for  $CF_E$ ,  $DF_E$  and no Beacon Exchange

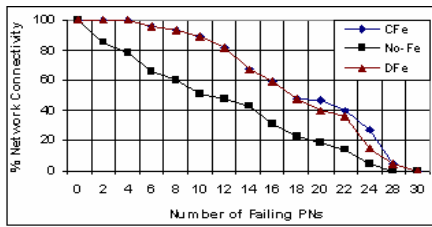


Fig. 4 Effect of Parent Node Failure on Network Integrity for  $DF_E$  and  $CF_E$  random load changes, the straight line ( $v = 1$ ) would perform better, and this is borne out in Fig. 5B where by inducing an equivalent change in  $F_E$  as the load changes keeps the network well informed about the network state, with lower control traffic than that of the logistic change. Conversely, when the network load underwent smooth changes from start to finish, it was found that inducing logistic change helped conserve bandwidth by minimizing control traffic as observed in the increasing and normal load profiles in Fig. 5B.

The reason for the improved performance of the logistic curve is found to be that for increasing and normal load profiles, the logistic curve updates exchange rate at a higher value (i.e. lower beacon exchange rate) earlier than the straight line. This earlier updating reduces traffic and conserves overall network bandwidth. Similar trends are observed in the case of random loads where the straight line performed better. It was found that the straight line established higher BER values quicker than the logistic curve which also reduced network traffic more quickly and for a longer period, making it suitable for random load situations.

#### D. 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.

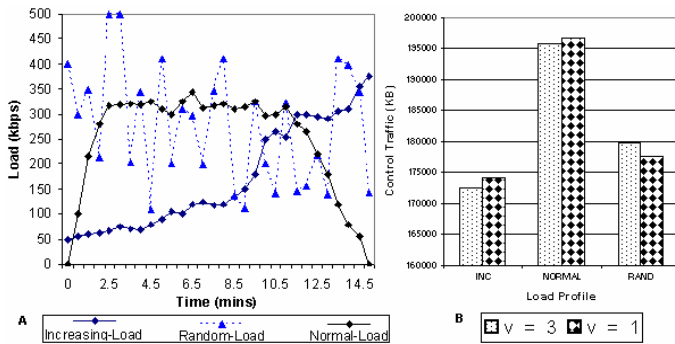


Fig. 5 (A): Increasing, Normal and Random Loads applied on the network to test the comparative performance of lambda curves, (B): Amount of control traffic generated by various load profiles for different  $\lambda$  curves

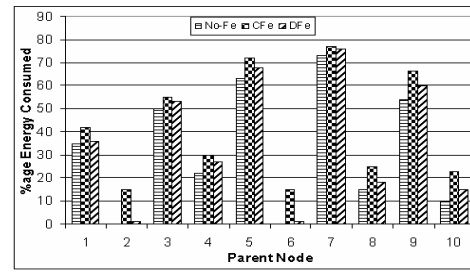


Fig. 6 Energy Consumption at various PNs for  $CF_E$ ,  $DF_E$  and no B/Exchange

#### IV. 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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