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An Energy-Efficient Routing Model for Scale-free Wireless Sensor Networks

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Scale-free Networks have surfaced as a significant discovery of network science with a wide application domain. The present paper explores scale-free network theory to design an efficient routing model for Wireless Sensor Networks. A dynamic wireless sensor network where nodes' degree distribution follows power-law is a Scale-Free Wireless Sensor Network. The evolving nature of Scale-Free Wireless Sensor Networks and huge traffic flow make routing challenging. The paper proposes a hybrid cluster-based Energy Aware Scale-Free (EASF) routing strategy which uses static and dynamic network parameters like node degree, betweenness centrality, and node residual energy for topology generation and routing in a scale-free wireless sensor network. The adaptive nature of the algorithm effectively relocates the load from highly congested nodes to other nodes in the network by using a route evaluation function. The proposed algorithm increases network lifetime by about 33% and 15% and achieves a high clustering coefficient of approximately 37% and 25% higher when compared with Flow Aware Scale Free Model and Local-Area and Energy Efficient Model respectively. The cluster-based forwarding of data packets in EASF helps achieve a smaller increase in average path length with an increase in network size in comparison to FASF and EASF models.

Keywords: Scale-Free, Wireless sensor network, Betweenness Centrality, Routing, Preferential attachment

1 Introduction

Wireless Sensor Networks (WSNs) comprise thousands of self-organized dynamic sensor nodes emplaced to monitor environments. Some of the issues with wireless sensor networks are limited battery power, unattended environments, limited transmission range, scalability, fault tolerance, and attack vulnerability[1-2]. The limited battery of sensor nodes gets depleted easily if a packet is transmitted frequently through only a few nodes in the network. This unbalanced energy consumption of sensor nodes leads to the formation of holes in the network which adversely impacts the performance of the whole network[3]. Achieving balanced energy consumption of nodes so as to establish a stable and robust wireless sensor network is an extremely important research issue. Sensor nodes consume energy during network generation as well as operation. Both aspects need to be taken into account while designing routing strategies for these networks.

Scale-Free Networks are self-organized evolving networks of inhomogeneous nodes with power-law degree distribution. One of the most basic scale-free models proposed is Barabasi-Albert Model[4] where nodes obey power-law degree distribution. The growth and Preferential principle guide the expansion of these networks [5-6]. There are a few nodes called hub nodes which have a very high degree when compared with other nodes in the network. The survivability ratio of these nodes is very good in case of random attacks, thereby increasing robustness of the whole network. The characteristic properties of SFNs are a high clustering coefficient, short average path length, and high robustness. The evolution scenario of a scale-free network with m_0=m=2 is shown in Figure 1.

In the last decade, scale-free network concepts have been used effectively across diverse and broad application domains such as communication networks[8-10], metabolic networks[14-15], social networks[7], Supply Chain Networks[11-13], citation networks[18], COVID 19 immunization models[16-17], WSNs[19-24]. The robustness and connectivity of Scale-free networks can be explored to design efficient routing schemes [30-31] for wireless sensor networks.

This paper incorporates the scale-free property to design an Energy Efficient routing strategy for wireless sensor networks. The proposed model employs static as well as dynamic parameters such as node degree, node residual energy, and betweenness

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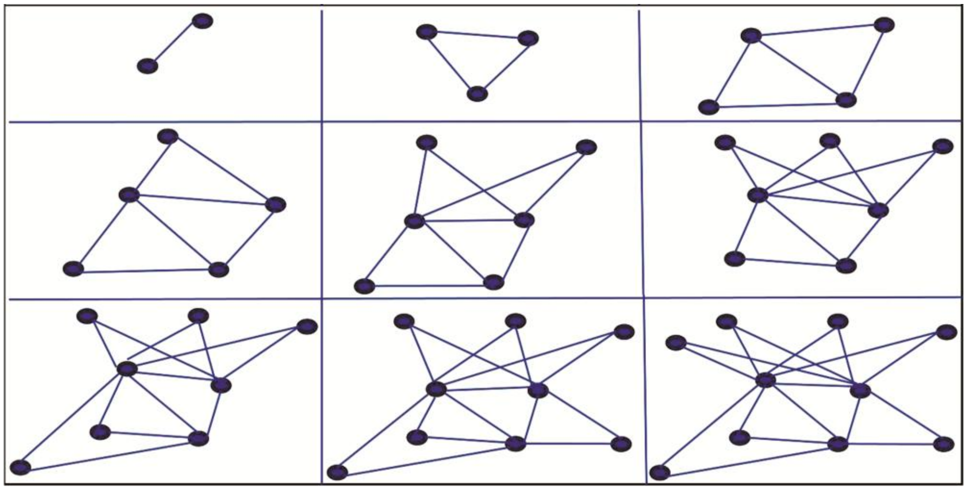

Fig. 1 — Scale-Free Network progression with time (mo=2 and m=2).

centrality for topology generation and routing in a scale-free wireless sensor network. The EASF model helps generate an energy-efficient topology for WSNs and also improves the random error tolerance of the network.

Section 1.1 of the paper presents the existing literature on scale-free wireless sensor network topology evolution and routing schemes. In section 2, the proposed Energy Aware Scale-Free routing algorithm (EASF) has been described. In Section 3, different simulation scenarios and results are presented. The last section of the paper summarizes the contribution of the proposed model and discusses some of the future research dimensions.

The topological advantages offered by Scale-Free Networks in terms of random error tolerance and connectivity have been a motivating factor in adopting scale-free theory for designing evolution and routing strategies for Wireless Sensor Networks. This section presents some of the research done so far in this regard.

For weighted WSNs, Flow Aware Scale Free Model (FASF)[21] has been proposed where node degree is used for preferential attachment. The amount of energy consumed by any node is directly related to the number of packets being sent/forwarded from that node. The traffic created by a new node in the immediate neighborhood is taken into account while incrementing the weight of an edge. It incorporates x new edges for every node/link that is damaged or removed in the network.

Another model based on node degree is given by Zhang Xuyuan et. al [20]. In Improved scale-free model for wireless sensor networks, the probability of new node being damaged and the transmission limitations of a sensor node are considered. A saturation constraint on the number of connections a node can have in the monitoring environment has been applied to ensure balanced energy consumption.

Hailin Zhu et al.[23] gave two models Energy Aware Evolution Model (EAEM) and Energy-balanced Evolution Model (EBEM) for WSNs based on scale-free theory. In EAEM, incoming node connects itself to an existing node in the network which has high residual energy and high connectivity within its local area. One of the challenges with this approach is sensor nodes have limited battery power and the nature of applications is such that they can not be replaced or recharged easily. Taking this into consideration, EBEM model was proposed where maximum connection limit is setup which is updated periodically on the basis of remaining power of the node. The network performance of EBEM is better when compared with EAEM. All these models are based on the inherent assumption that all nodes in WSNs are equivalent, thus not suitable for many real-world applications.

In cluster-oriented/inhomogeneous WSNs, sensor nodes monitor the environment and submit the data to cluster heads which send it to sink for further action. To account for this node and link heterogeneity, Shudong Li et. al[24] postulated local world heterogeneous model of WSNs which identifies two types of nodes a regular node and a cluster head node. The authors carefully studied the diversity in nodes/links deployed in a WSN environment so as to bound the number of connections in the network An incoming known role is identified on the basis of cluster head ratio. For different values of cluster head ratio, the impact on network performance metrics like average hop count and degree distribution has been examined.

To achieve more balanced energy consumption in the network, Nan Jiang et. al[25] gave the concept of Local World in a large scale WSNs. The communication pattern between different nodes in the network is studied to account for energy sensitivity of nodes.

Another model based on local world is given in[26], Local Energy Efficient Model (LAEE) where node transmission range defines its local area. From a scattered network, the topology evolution starts on the basis of energy-based preferential principle. The degree distribution of nodes exhibits scale-free features in this model. Sometimes, sensor nodes are emplaced in hostile inaccessible areas where they are damaged or lose energy frequently. Therefore, a node/link compensation mechanism has been included in Neighbourhood Log-on and Log-off model[22]. When a node loses some link, it initiates new links and gets preference when new nodes are added in the network.

Ying Duan et. al[27] included the features of both small-world networks and scale-free networks to give cluster-based evolution model for WSNs. Preferential attachment rule is based on node remaining energy and connectivity. Several placement schemes to create a connection between cluster head and sink nodes have been introduced to reduce average path length and prolong network lifetime. One of the drawbacks of the scheme is that shortcuts cannot be inserted anywhere in the network but are dependent on real network environment.

The structural properties and dynamicity offered by scale-free networks can be applied while designing efficient routing protocols in WSNs[29]. Xiao Hui Li et. al[28] propounded an energy-aware routing strategy for weighted scale-free WSNs based on betweenness centrality. The weight of the link is dependent on betweenness centrality[32-35]. To prolong network lifetime, traffic from central nodes i.e., nodes with high betweenness is shifted to nodes with low betweenness.

Several promising models have been presented so far, yet there is scope for improvisation. Many of the current models are based on homogeneous WSNs where the real application environment is mostly inhomogeneous. Most of existing models for topology generation have given equal weightage to connectivity and energy in the network but different proportions can be assigned to both according to application. There are very few strategies that incorporate scale-free features while designing routing function for scale-free WSNs. Hybrid routing protocols which combine the global and local routing parameters have not been fully explored. Therefore, we propose hybrid cluster-based Energy-Aware Scale-Free Model for WSNs inspired by scale-free theory.

2 Materials and Methods

In this section, different assumptions, and workflow process of the Energy-Aware Scale-Free model (EASF) for Scale-Free WSNs is presented.

2.1 Assumptions

- Initial connected seed network of CH_0 cluster nodes and e_0 links
- Transmission range of the node limits the communication capacity of the node
- Each cluster head has at least one route to the base station
- Inhomogeneous nodes (Sensor nodes, Cluster_Head and Base_Station)

2.2 EASF Topology Evolution Scheme

The proposed EASF model performs two functions topology generation and routing. The model considers inhomogeneous nodes namely sensor nodes (n), cluster heads (CH), and Base_Station in the network. These nodes differ in their initial energy, memory and processing capacity making the network heterogenous.

The sensor nodes sense and submit the data to cluster heads which then further transmit it to the base station. The Base_Station is located at the center of the network. The EASF model is designed as below:

Step 1:Network Initialization: Scale-free network is formed with initial seed network of c_0 cluster nodes and e_0 links. each cluster head has at least one path through which it can communicate with the base station.

Step 2: Network Growth: A new node either cluster head or sensor node with m edges is introduced in network periodically. The possibility of new node being a cluster head is denoted by h.

*Step 3: Fitness Evaluation:*Incoming sensor node 'i' build potential local_world (LW) by exchanging hello messages. Upon receiving the message, cluster nodes *(CH_j)*in the transmission range *(Tr_i) of i* evaluate their fitness on two parameters, namely, degree centrality and residual energy. Only those cluster nodes which have not yet reached the degree saturation limit K_{sat} and have remaining energy more than the energy threshold value (E_{Th}), feedback on their connectivity status. The graphical representation of EASF model is given in Figure 2.

1. *Incoming_Nodei broadcasts HELLO message*
2. *For each CH_j in Tr_i*
3. *If (K_j<K_{sat}) && (Er_j>= E_{Th})*
4. *Feedback Connectivity status*
5. *End*
6. *Add J in LW_i*
7. *End*

Step 4: Preferential Attachment: The incoming sensor node attaches itself to the existing cluster head node in accordance with preferential attachment rule based on node degrees and residual energy as given in Equation (1).

$$\pi_i = \pi_{local-world}\left[\alpha \frac{K_i}{\sum_{x=1}^{N(t)} K_x} + (1-\alpha)\frac{E_i}{\sum_{x=1}^{N(t)} E_x}\right] \quad \dots (1)$$

Where, α is a tunable parameter that determines the proportionate weight of node degree and node remaining Energy, N(t) is the number of CH within range of new node, K_x is degree of node x, E_x is the remaining energy of node x. For α=0, node with the highest remaining energy is selected as the target node and α=1 selects node with largest number of connections. If the income node is a cluster head, then it preferentially attaches itself to an existing cluster head based on its connectivity and residual degree. The number of cluster heads in the network should be selected judiciously as more cluster heads would increase the expenses of the network establishment and very few cluster heads would lead to operational overload of such cluster heads. The flow diagram of the EASF topology evolution process is given in Figure 3.

2.3 Proposed Routing Scheme

An efficient routing protocol for scale-free wireless sensor networks should consider nodes' network dynamicity and energy sensitivity while identifying the most suitable path from sensor nodes to the base station. Taking this into account, the EASF model postulates a cluster-oriented hybrid routing scheme for efficient multi-hop data delivery in a scale-free wireless sensor network. The flow diagram of the EASF routing scheme is given in Figure 4.

The proposed algorithm is a hybrid scheme as it considers static and dynamic parameters while selecting the optimal routing path. The routing function is based on residual energy and betweenness centrality of existing nodes in the network. Betweenness centrality of a node n (BC_n) represents the number of shortest paths passing through that node in the network as given in Equation (2).

$$BC_n = \sum_{x \neq y} \frac{\sigma_{xy\ (n)}}{\sigma_{xy}} \quad \dots (2)$$

Where, $\sigma_{xy\ (n)}$ is the number of shortest paths passing from source (x) to destination(y) with j as intermediate node.

Sensor nodes in the network generate data packets and send them to their respective cluster head for further transmission. Route (P_{sd}) from cluster head to

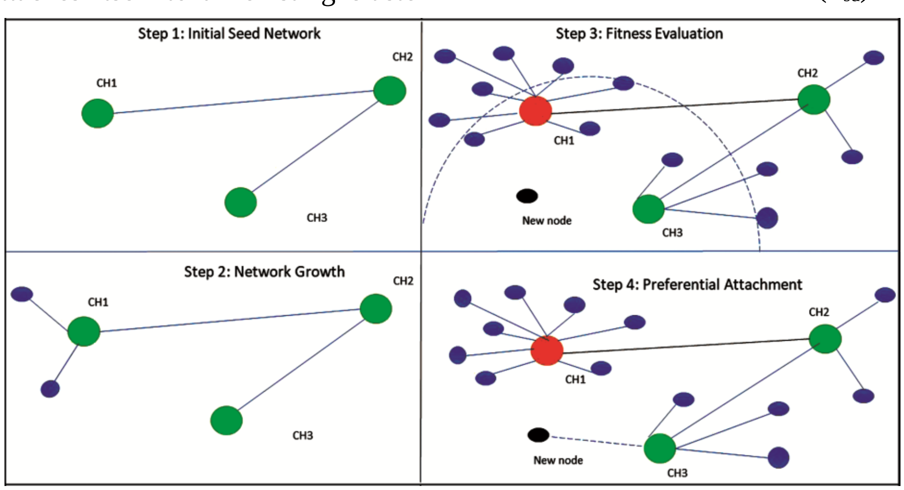

Fig. 2 — Graphical Representation of EASF.

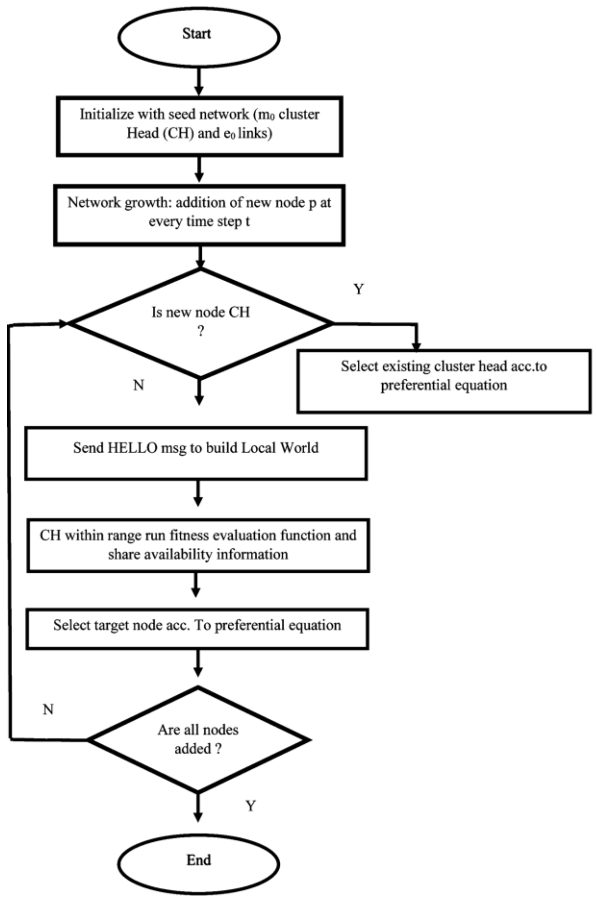

Fig. 3 — EASF topology evolution process.

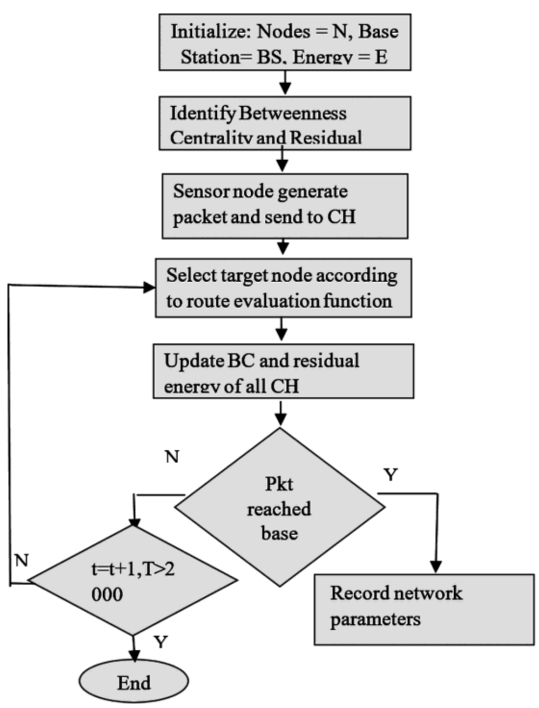

Fig. 4 — EASF routing process.

base station is selected in accordance with the routing function given in Equation (3)

$$P_{sd} = \max \sum_{x=0}^{l} [b * N_{BC}(x) + (1-b) * N_{Er}(x)] \quad \ldots (3)$$

Where, b is an adjustable parameter that determines the proportional weight of betweenness centrality and node residual energy. $N_{BC}(x)$ is the normalized betweenness centrality of node x and $N_{Er}(x)$ is the normalized residual energy of node x. Normalized Betweenness Centrality of a node is defined as the ratio of betweenness centrality of a node over maximum betweenness centrality in the network as shown in Equation(4)

$$N_{BC}(x) = \frac{BC(x)}{\max(BC)} \quad \ldots (4)$$

The normalized residual energy of a node n is the ratio of residual energy of node n to the maximum residual energy in the network as given in Equation (5).

$$N_{Er}(n) = \frac{Er(n)}{\max(Er)} \quad \ldots (5)$$

The tunable parameter ensures a balance between betweenness centrality and remaining energy of nodes as the effect of shortest path cannot be avoided entirely. Transmission of packets through only nodes with high betweenness may lead to quick exhaustion of their energy whereas considering only residual energy may adversely increase path length. The diversity in path selection ensures efficient utilization of resources and dodges hotspots in the network to prolong network lifetime.

3 Results and Discussion

This section comprises different simulation scenarios and accomplished results for EASF model. The performance of the EASF model in terms of network lifetime, clustering coefficient and average path length is analysed and compared with Flow Aware Scale Free Model (FASF) and Local-Area and Energy Efficient model (LAEE). Table 1 specifies the different simulation parameters.’

The variation in proportion of available nodes with different values of tunable routing parameter ‘b’ is presented in Figure 5. As evident from Figure 3, the optimum value of parameter b=0.4, where we have the maximum number of available nodes in the network. The descending rate of the proportion of

Table 1 — Simulation Scenario

Parameters	Value
Simulator	MATLAB
Initial seed network (m_0)	3
Number of nodes	500
No of edges of new node (m)	1
Cluster-head ratio (h)	0.2
EnergyConsumption Model	First Order Radio Model [33]
Grid Size	200x200
Transmission range	20m
α , b	0.3,0.4

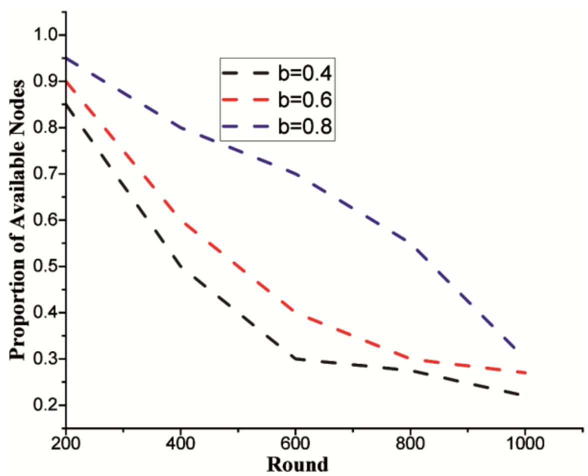

Fig. 5 — Proportion of available nodes with different values of 'b'.

available nodes is less when the remaining energy of the nodes is given due weightage while selecting an efficient path in the network.

The comparative analysis of EASF in terms of clustering coefficient is presented in Figure 6. The clustering coefficient of the network represents the connectivity of the network. For a node x, it depicts the proportion of actual links to the maximum links possible between node x neighbours, $C_x = \frac{2E_x}{K_x(K_x-1)}$. Higher the value stronger the connectivity. With increase in network size, the clustering coefficient for all the models decreases but the rate of reduction is less in EASF when compared with FASF and LAEE.

Figure 7 represents variation in average path length with increase in number of nodes (100-500) for all the three models. From the graph, we observe rate of increase in path length with increasing network size is less for EASF when compared with FASF and LAEE. The cluster-based forwarding of data packets and inhomogeneous nature of nodes in EASF helps achieve smaller average path length. The route in proposed algorithm is selected in a way that it avoids the traffic hotspots in the network.

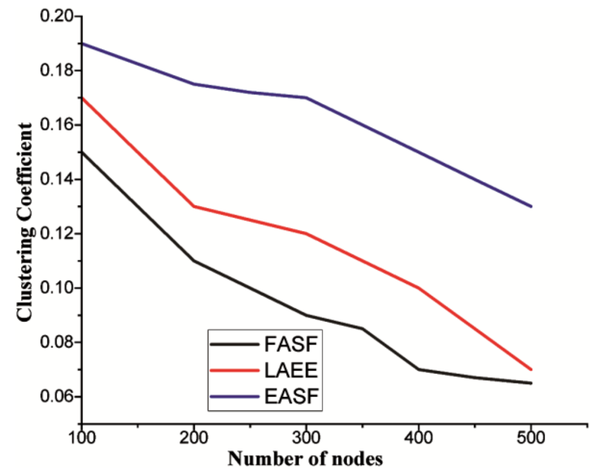

Fig. 6 — Clustering Coefficient vs. number of nodes for EASF, FASF and LAEE.

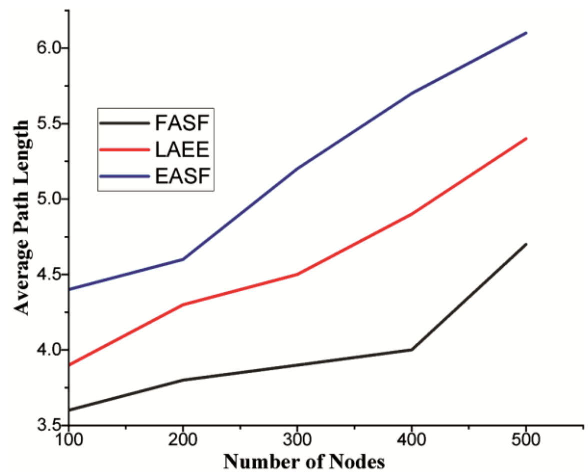

Fig. 7 — Average path length vs. number of nodes for EASF, FASF and LAEE.

The proportion of available nodes in successive rounds is used to analyse the Network Lifetime of different models as shown in Figure 8. Network lifetime is the time between network initiation to the point where first node dies.

Due to the multilevel transmission of data, consideration of betweenness centrality and node residual energy during topology evolution and data transmission in the proposed model, it outperforms the other two models in terms of number of available nodes. More availability of nodes also represents the stability of EASF model. FASF model does not consider the limited energy of sensor nodes while generating topology which limits the lifetime of the network. LAEE model does not consider the inhomogeneity of the sensor nodes in the network.

The effect on average path length with the random removal of nodes in the network is depicted in

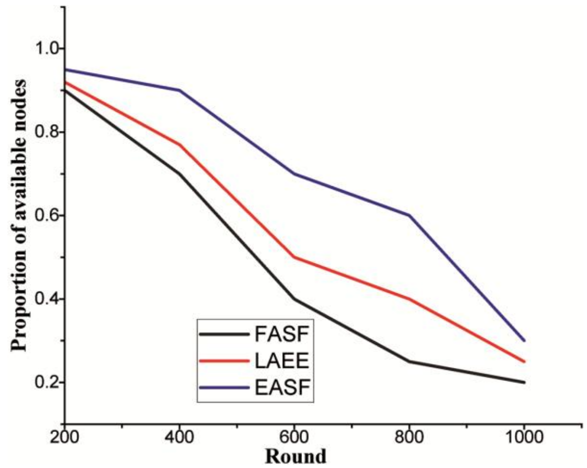

Fig. 8 — Comparison of network lifetime for EASF, FASF and LAEE.

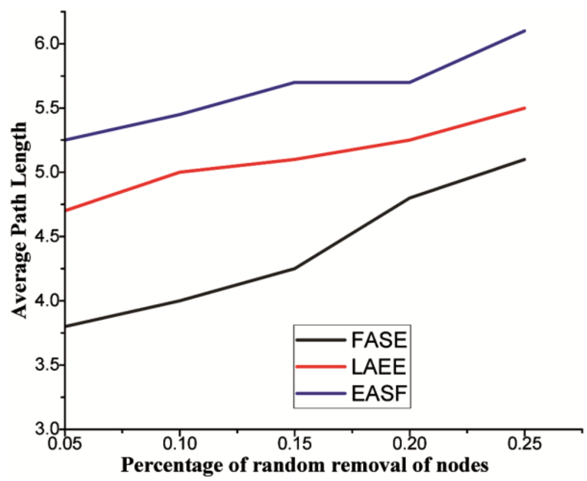

Fig. 9 — Average path length vs. Percentage of random removal of nodes for different models.

Figure 9. The capacity of any network to withstand failures represents its robustness. As evident in Figure 9, the average path length of all the models increases with increase in proportion of random removal of nodes. EASF model outperforms the other models due to the presence of cluster heads and the inherent scale free structure of the network.

4 Conclusions

The nodes in WSNs are energy constrained, and extending the lifetime of such networks is a very exigent issue. This paper proposes the Energy-Aware Scale-Free Routing Model for Wireless Sensor Networks where static and dynamic parameters namely, node degree, node residual energy, and betweenness centrality of nodes are used for topology generation and routing. The proposed model adopts a cluster-oriented scheme where an incoming node preferentially attaches itself to the existing cluster head in its range with maximum degree centrality and residual energy. Moreover, the degree saturation limit has been imposed to avoid too many nodes getting attached to a single cluster. The proposed model efficiently distributes the traffic from central nodes in the network to other nodes to avoid creating energy holes in the network.

- The network lifetime with the EASF model increased by approx. 33% compared with the FASF model and approx. 15% compared with LAEE model.The route selection procedure carefully distributes traffic across different paths available to avoid congestion hotspots, thereby increasing the network lifetime.
- The clustering coefficient of EASFmodel grows by about 37% and 25% compared with FASF and LAEE model.Periodic updating of parameters like node residual energy does incur some delay in the network but does not aggravate the network performance.
- By varying the value of the tunable parameter ‘b’, the model can be applied to a wide range of fields Industrial Automation, Healthcare systems and Environment monitoring.
- In the future, an appropriate mechanism to account for node failures and the concept of redundant nodes may be incorporated to further improve fault tolerance of the network. Priority-based traffic transmission can be included in the proposed model to suit time-sensitive applications. The performance of the proposed strategy with different placement of sinks in the network may be analyzed to prolong the network lifetime.

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