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Error Prediction Scheduling for Energy Efficient Routing in Wireless Sensor Network

Patil Yogita Dattatrayaá[1], Jayashree Agarkhed[2] and Siddarama R. Patil[3]

Abstract: Sensor nodes in Wireless Sensor Network (WSN) can be deployed in dynamic environment due to their self monitoring and dynamic scheduling property. Scheduling among sensor nodes helps to save energy. Many techniques are proposed to save energy by turning off sensor nodes at the cost of low sensing fidelity by introduction of sensing gaps. Sensing error, one of the performance parameter is not highlighted much in the previous literatures. We proposed an efficient sensing by error prediction scheduling algorithm called as EPSEER which is based on inferred sensing error among collaborative nodes. Neighborhood nodes can trigger sensing activities when inferred error has exceeded the tolerable sensing error. Our proposed scheduling approach provides data accuracy and energy efficient routing that can be used for monitoring applications in dynamic environment.

1. INTRODUCTION

WSN has gained worldwide attention since from many years and in turn has lead to development of smart sensors with limited processing capability and computing resources. These sensor nodes can sense, measure and gather information from environment based on some local decision process. WSN have wide range of applications in the fields like military environment condition monitoring, factory and process automation, home automation and tracking of objects, animals, humans, and vehicles etc. One major source of power consumption is energy cost of sensing activities. Many applications [1] require sensor nodes to sustain for weeks or evenly months together. Thus there is need to avoid unnecessary sensing activities in order to extend the lifetime of sensor nodes. This can be achieved by developing scheduling algorithm to turn on the sensor when required and turn off the sensor whenever not required to save energy.

Lot of research work as been carried out on collaborative sensing [2-6]. These previous works specify efficient way to select or deploy a minimum number of sensor nodes to provide better coverage. All these works focus on sensing activities based on coverage requirements in time and space. They have not forced on how to schedule sensing activities based on sensing error and hence fails to provide data accuracy within desirable bounds. In this work we have used both dynamic scheduling based on sensing error among collaborative sensors to optimize tradeoff between energy consumption and accuracy of predictions which has advantages over existing single node scheduling methods [7].

The detailed analysis of the simulation proves that proposed method can save energy and it is able to confine sensing error within precise error tolerance.

The overview of related work is discussed in section II. Methods to implement proposed work discussed in section III. Section 4 highlights on results and discussions. Section V concludes the paper.

[1,2,3] P.D.A College of Engineering, Kalaburagi, Karnataka–585102, India, Email: áagyogita@gmail.com, jayashreeptl@yahoo.com, pdapatil@gmail.com

2. RELATED WORK

Sensor nodes are scheduled for data transmission, provide an effective way to conserve energy. It also reduces transmitting and sensing power while preserving sensing quality. Sensor deployment pattern must provide full coverage and K-connectivity considering ratio of sensor communication R_c to sensing range R_s for homogeneous WSNs [3]. The earlier proposed methods do not provide optimal patterns and also failed to provide high throughput and packet loss. Full coverage 3D sensor network provided by use of 14-and 6-full connectivity [5] with compromise of less throughput and packet loss. Another important parameter to increase lifetime of sensor node is to reduce power consumption. With sensing and scheduling algorithm called CIES in [7], nodes can share sensing error information and can collectively control sensing errors through neighborhood coordination. Also network can respond to dramatic environment changes more quickly. Thus it can be used for monitoring applications to provide high data accuracy while conserving energy. CIES considers error interference. The error information not only used by local sensing scheduler but is also shared among neighbors. Nodes can trigger additional sensing activities of the other neighbor nodes when the inferred error has aggregately exceeded the error tolerance [8]. CIES approach use local error control algorithm to assure a specified error bound and neighbor error control to adjust duty cycles of sensor nodes.

Dynamic power management techniques [9] allow applications to manage sleep and idle status by dynamic power management of sensor nodes. In [10] author proposed and evaluate a novel data correlation-based stochastic scheduling algorithm, called Cscan by integrating an empirical data prediction model with a stochastic scheduler to adjust a sensor node's operational mode to achieve substantial energy savings. Collaborative sensing model in [11] support integration of WSNs and mobile phones flawlessly but use more bandwidth and has high overhead. Energy wastage has been minimized by keeping only small number of sensor nodes active at a particular time while others are kept in sleep mode by use of minimum size connected K-coverage method [12].

A group of sensor M in which particular sensor network is covered at least by K different sensors present in sensor group generated by M is connected. This method has computation overhead and fails to provide proper scheduling among sensor nodes. In [13] author presented an energy efficient framework for cluster based data collection in wireless sensor networks by integrating adaptively enabling/disabling prediction scheme. In [14] author has proposed a priority list sensor scheduling (PLSS). This approach facilitates efficient distributed estimation in sensor networks, even in case of unreliable communication, by prioritizing the sensor nodes according to local sensor schedules based on the predicted estimation error. PLSS minimizes the expected estimation error for arbitrary packet-loss or transmission probabilities.

In [15] author exploited temporal-spatial correlations among sensory data. The author focused on basic concept that a sensor node can be turned off safely when its sensory information can be inferred through some prediction methods, like Bayesian inference. Also the concept of entropy in information theory to evaluate the information uncertainty about the region of interest (RoI) is considered. In [16] consider synchronization, scheduled communications rendezvous, and packet acquisition. Synchronization accuracy worsens with prediction interval, saves energy by enabling scheduling, but costs energy to maintain it. In [17] author presented an energy-balanced multiple-sensor collaborative scheduling for maneuvering target tracking in wireless sensor networks (WSNs). It provides better performance in saving energy and energy balance than the dynamic collaborative scheduling scheme. In [18] propose two novel dynamic duty cycle scheduling schemes (called DSR and DSP) in order to reduce sleep latency, while achieving balanced energy consumption among sensor nodes in wireless sensor networks

3. PROPOSED WORK

Findings of extensive literature survey as motivated to achieve following objective:

- To develop generic scheduling mechanism based on sensing error inferred during sensing activity.
- To provide accuracy of error prediction and also to provide high data accuracy among collaborative sensor nodes with optimized energy utilization for highly dynamic environments.

These objectives are achieved by cluster based architecture shown in fig. 1 for energy efficient routing and Error Predictor System shown in Fig. 2 for EPSEER.

In the Fig. 1 primary cluster head (CH) is select as node with highest residual energy for every around of Time period T along with sub cluster formation and respective sub cluster heads (known as duty cycle controller) selection among the node in range R of sub cluster. Sub CH uses Error prediction system shown in fig 2 to schedule node in sub cluster for energy balancing among cluster member nodes.

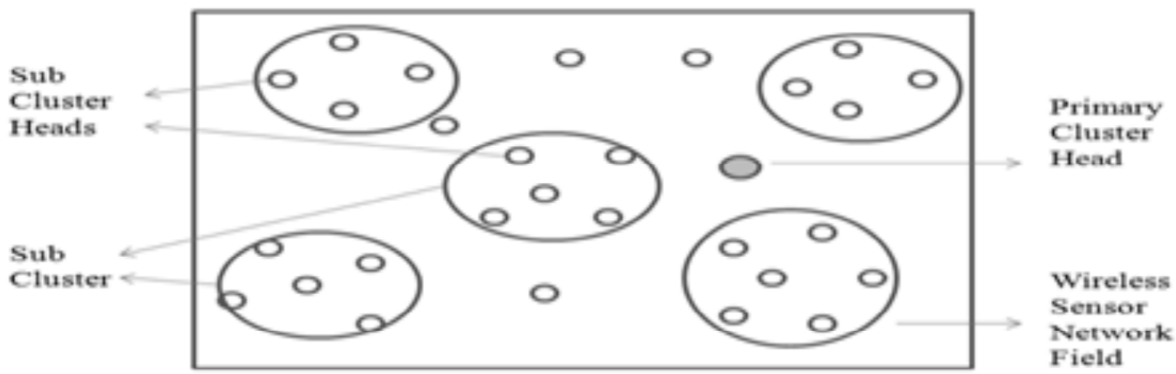

Figure 1: Cluster based architecture for node energy balanced routing

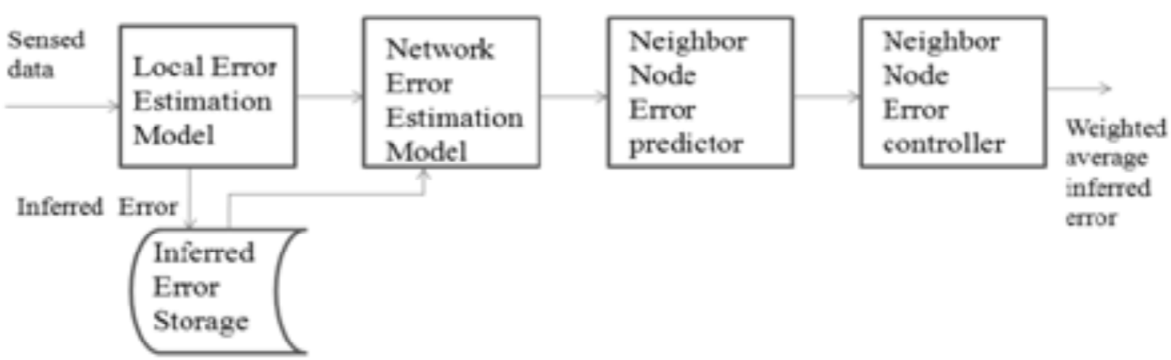

Figure 2: Error Predictor System for EPSEER

Error Predictor System shown in Fig. 2, includes module for proposed system discussed in the following subsection.

3.1. Local Error Estimation model

Local error estimation model is referred as non collaborative method, which mainly uses only duty cycle controller and a local error predictor. The existing system that is eSense uses this method. It uses a local error predictor in order to predict the errors without performing any sensing activity. When data is obtained through actual sensing operation, that value is compared with the value obtained by local error predictor and the value is stored in local error data library. Based on the error prediction, duty cycle controller adjust the sensing frequency. This Duty cycle controller will adapt the system to various errors inferred by different prediction model and the local error estimation model will be as a reference for duty cycle controller for further analysis. In previous existing system, only one node among the nodes in WSN, with maximum residual energy was elected as duty cycle controller. This lead to inefficient energy utilization, as it burdened duty cycle controller maintaining status of all nodes throughout the data transmission phase. To overcome this problem in EPSEER, role of duty cycle controller has been assigned to another node with maximum residual energy among the nodes in individual clusters for each round of time period T. This helps to achieve balanced energy conservation of nodes in sub cluster.

3.2. Network Error Estimation Model

Since the local error estimation process does not work when there is dramatic change in the environment and it also gives high prediction error. In order to reduce prediction error a better error prediction method is used which is known as network error estimation method. It uses collaborative inferred error sensing method which minimizes the prediction error. The error is inferred with respect to the neighbor node. The duty cycle controller senses the transmission range and it adjusts the transmission range with the help of antennas and connectivity. In order to provide prediction and information sharing among the neighbor nodes we use two processes in the network error estimation model. They are neighbor node error predictor and a neighbor node error controller.

3.3. Neighbor Node Error predictor

The neighbors can change dynamically so there is need to iteratively estimate the neighbor's prediction error by following steps.

- **Step 1: Neighbor Node Identity: S**ensor recognizes a node as its neighbor which is closer to it
- **Step 2: Node-pair Weight Calculation:** Here data correlation between the nodes is calculated and each nodes at the end of each round exchanges its observation with the neighbor node. The average sensing correlation between nodes is calculated as node-pair weight w_{ij} that indicates how similar the sensing observation is between two neighbor nodes *i* and *j*.
- **Step 3: Achieving the inferred error e_{ij} for neighbors:** we can predict error of neighbor nodes using local prediction errors and can infer the prediction error of correlated neighbor nodes as, given a node i and its neighbor node *j*, the node-pair inferred error e_{ij} can be defined as the inference error at neighbor *j* from the point view of node *i*.

3.4. Neighbor Node Error controller

After estimating the error value for neighbor sensor *j*, sensor *i* send the inferred error *eij* to neighbor node error controller process, where the error information is sent and received. The neighbor node error controller calculates weighted average inferred error. Given a neighborhood G (V, E) a sensor node *j*'s weighted average inferred error *ej*. This is *ej* is the weighted average of all node-pair inferred errors, i.e., *eij*, where *i* and *j* are neighborhood pair. Weighted average inferred error calculated as,

$$e_j = \sum_k e_{kj} \times \frac{W_{kj}}{\sum W_{kj}}, k \in N(j) \tag{1}$$

Where,

k is size of the neighborhood of the node *j*,

W is the node-pair weight

N(*j*) is the neighborhood list of node *j*.

After detecting the error i.e. the distance with respect to the neighbor nodes, their transmission ranges is sensed by the duty cycle controller and the transmission ranges is adjusted with the help of antennas and the sensor nodes are brought within the sensing probability bound, thus providing sensor collaboration and achieve network connectivity. After predicting the errors with respect to neighbor nodes accurately and bringing the nodes within the sensing probability range with the help of Network node error control, the routing phase is designed in order to route the packets from source to destination.

3.5. Routing

For routing purpose AODV protocol implemented. It sends the route request and reply packets to find the route to the destination. When the routes are available, the shortest path to the route is chosen using dijkstra's algorithm. Finally the packets are sent using this shortest path. The algorithm 1 illustrates working of proposed system.

The error prediction system for scheduling node of WSN has been incorporated in the algorithm to provide energy efficient data transmission in cluster based WSN

Algorithm 1: Error Prediction Scheduling for Energy efficient routing

Step 1: Deploy homogeneous sensor nodes.

Step 2: Identify neighbor nodes by sending hello packet.

Step 3: For each round of time period *T*.

Step 3.1: Evaluate each node's residual energy.

$$E_{rem} = E_0 - \sum_{i=1} E_i \tag{2}$$

where,

E_0: initial energy

Ei: energy of sensor node at i[th] transmission time

Step 3.2: Select Primary CH as node with highest energy.

Step 3.3: Primary CH forms cluster of nodes that are within range *R*.

Step 3.4: Select duty cycle controller as a node with highest energy among the node's in each cluster.

Step 4: Calculate inferred error at each node

Step 4.1: Inferred error at node *i* is difference between sensed data and predictor value

Step 4.2: Compute worst error at node *i* as

$$PMF_i(e_i) = \int_{-e_i}^{e_i} \rho(x) d_x \tag{3}$$

where,

PMF is Probability Mass Function on e_i

e_i: observation error at node *i*

Step 4.3: Compute at sensor node *i*, inferred error of a neighbor sensor *j* as,

$$e_{ij} = PMF_j^{-1}(PMF_i) \tag{4}$$

Step 5: Calculate inferred error at neighbor node.

Step 5.1: Compute node-pair inferred error e_{ij}

Step 5.2: Compute weighted average inferred error e_j for sensor node as in eq. (1)

Step 5.3: If e_j and E_{rem} >threshold value then//neighbor node *i* of sensor node *j* violates data accuracy

Step 5.3.1: Sensor node *j* sent to active mode by duty cycle controller by adjusting *j*'s sensing range

Else

Step 5.3.1: Node *j* is in sleep mode

Step 5.4: Repeat step 4 to step 5 until data transmission is complete or till time period *T* completes.

Step 6: After time period *T* go to step 3.

Step 7: Collect the statistics for performance analysis.

Error Prediction Scheduling for Energy efficient routing-

Step 1 performs deployed of nodes in WSN randomly using random deployment process. Here nodes are assumed to be homogeneous. Step 2 after deployment, the neighbor nodes send the hello packets to ensure their availability. In step 3 residual energy of each node is calculated and primary cluster head is selected with highest energy for each round of time period T. Next sub clusters are formed by grouping node in certain range and sub cluster head called duty cycle controller which carries out error prediction method for scheduling node is selected in each sub cluster. In Step4 local error estimation model uses the local node error predictor which consists of duty cycle controller and an error analyzer. This duty cycle controller senses the transmission range and adjusts the range with the help of antennas. The local error predictor results in high prediction error and cannot work when there is sudden change in the environmental behavior. Therefore in step 5, we go for neighbor node error prediction where the error i.e. the distance is inferred with respect to the neighbor nodes and the duty cycle senses the transmission range and the range is adjusted with the help of antennas. The sensor nodes are brought within the probability range for high sensing and are schedule to be in active and sleep state to support energy efficient transmission. The shortest path to the destination is chosen and the packets are forwarded to destination.

4. RESULTS AND DISCUSSIONS

Based on three matrices the quality of sensor network is evaluated.

- **Error Rate**: It is defined as error rate that the prediction system produces.
- **Miss Ratio**: It is defined as ratio that the sensor system fails to respond to an event in rapid changing environment.
- **Energy Consumption**: It is defined as the total energy consumed by the network during its operation.

The simulation graph provides analysis of EPSEER for being energy efficient and provides optimal routing by selectively turning off sensor node in each sub cluster.

Here the error rate is at least 20% less than the non collaborative method hence it has achieved the performance requirements

Here the miss ratio is about 25% less with the non collaborative method. Hence it satisfies the performance requirement.

Here graph shows that compared to 25% error rate improvement in EPSEER, the additional energy consumption is small as the maximum difference between the two methods is less than 5% as shown in the graph below which is acceptable.

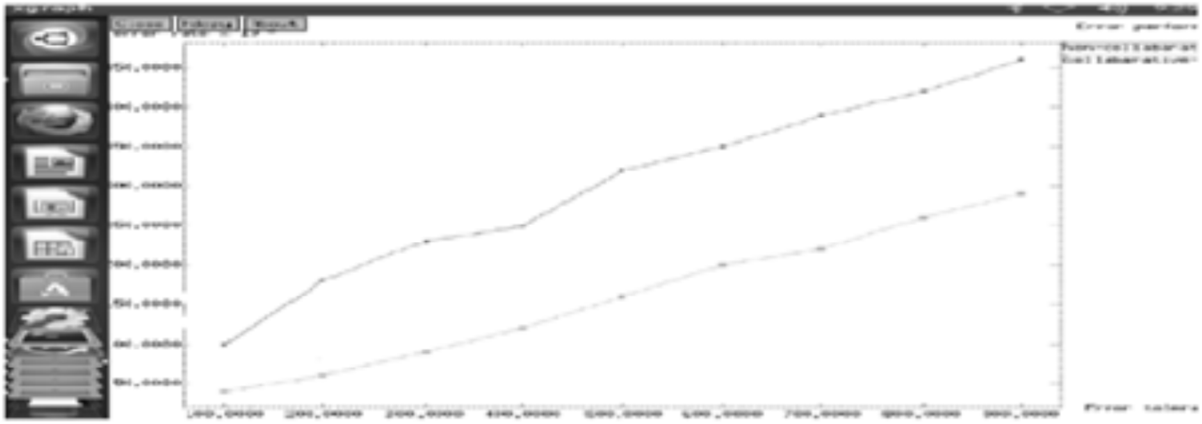

Figure 3: Illustrates the comparison of the error performance of non collaborative and EPSEER method with respect to error tolerance.

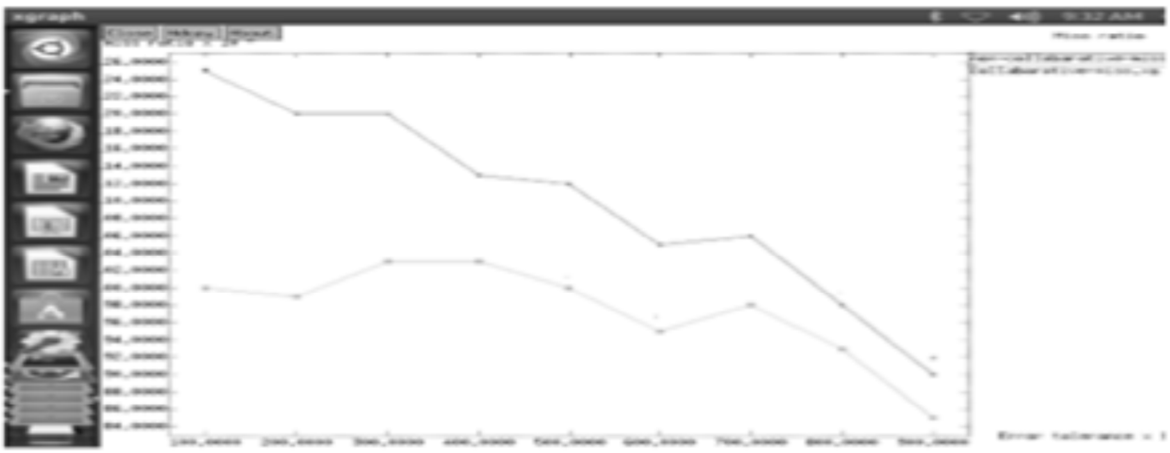

Figure 4: Demonstrates the metric miss ratio which is compared with the non collaborative and EPSEER

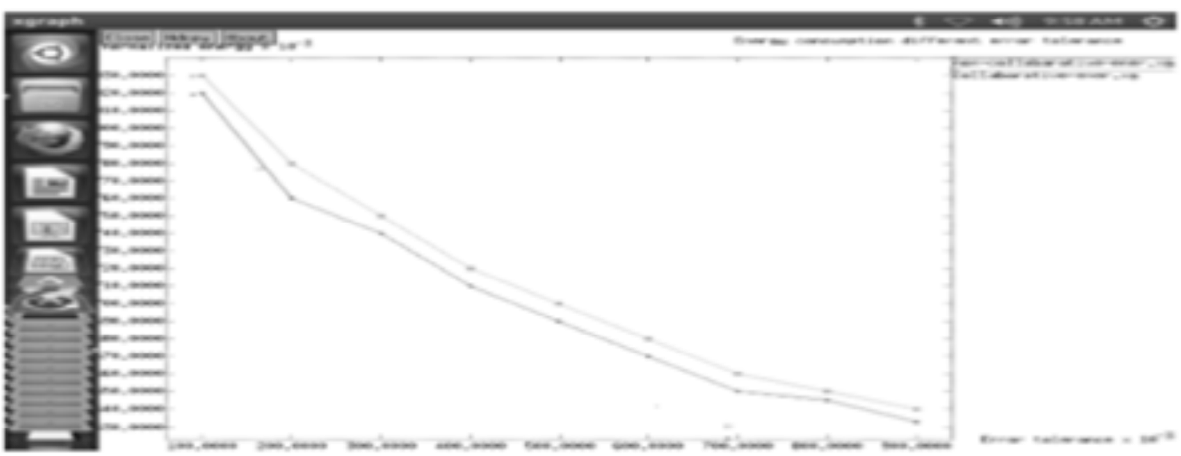

Figure 5: Error rate improvement in EPSEER

Here graph shows that error rates are reduced since there is greater chance for the sensor to be awakened by neighbor nodes when the node density is increased to 20.

Here graph demonstrates that miss ratio is reduced almost by 45% for different levels of error tolerance.

The graph shows that the Energy consumption is more but it is acceptable because the miss ratio and error rates are reduced and it is application choice to balance the trade-off between energy consumption and accuracy in the prediction of error.

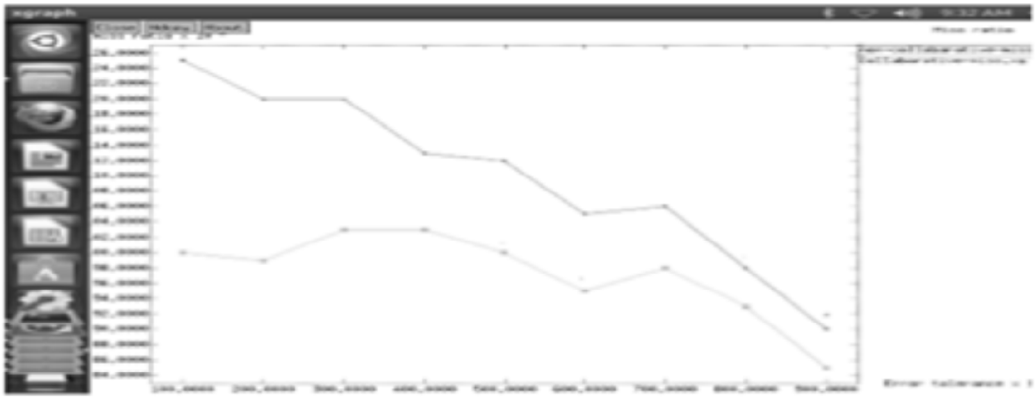

Figure 6: Error rate reduction by increase in node density

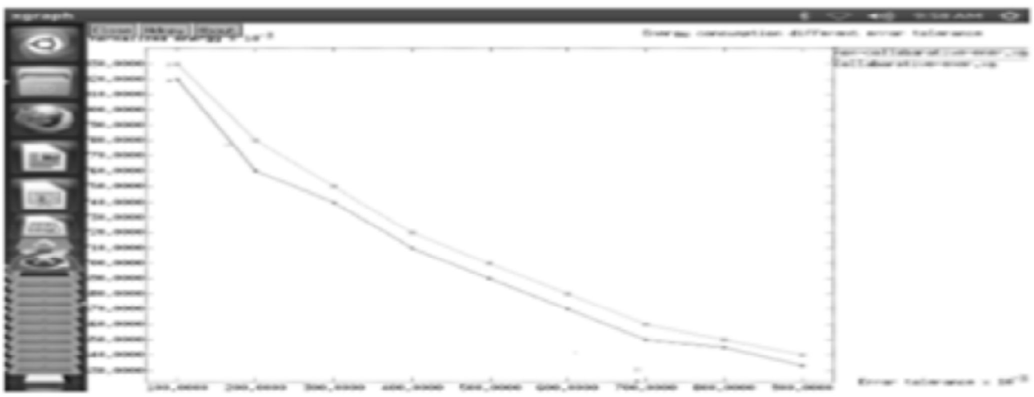

Figure 7: Miss ratio reduction for different levels of error tolerance

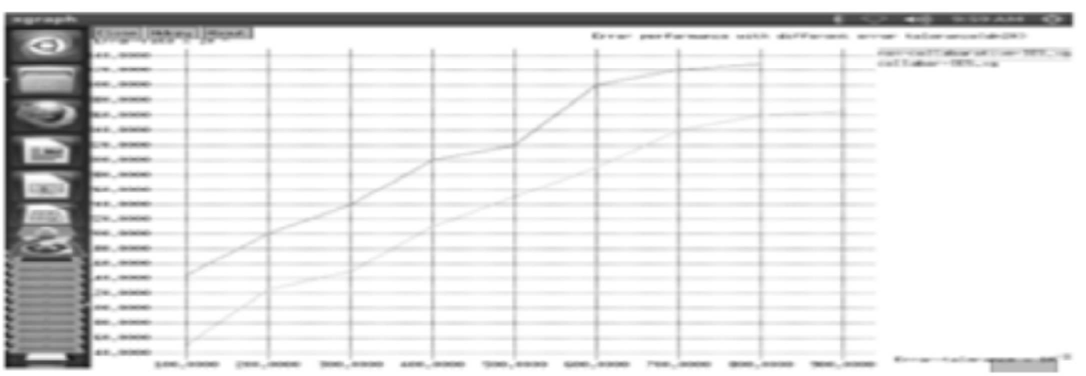

Figure 8: Energy consumption tradeoff with accuracy

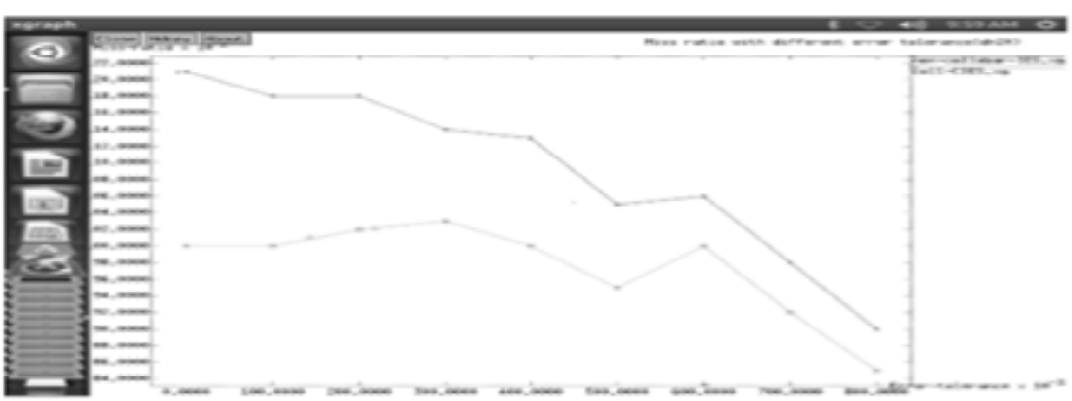

Figure 9: High Packet delivery Ratio using EPSEER

The graph shows that EPSEER achieves high packet delivery ratio.

5. CONCLUSION

To optimized energy balanced routing the need was to developed efficient sensing and scheduling algorithm. This objective is achieved by EPSEER using inferred sensing error among sensor nodes. Compared to existing approaches, the proposed approach meets all performance requirements i.e. with respect error tolerance and miss ratio. The results also show that error bounded scheduling is achieved providing better data accuracy and energy saving. In the proposed system a routing mechanism is also developed using AODV routing protocol and a shortest path is chosen using Dijkstra's algorithm to transmit the packet to the destination. The tradeoff between energy consumption and accuracy in the prediction of error can be overcome in future by offloading functionality of Network Error Estimation model and also by using better routing approach.

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