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Maximization of hard N-of-N life time and Accuracy of Wireless Sensor Networks

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Abstract **- Wireless Sensor Networks is a composition of distributed sensors that are capable of signal detection or classification. The previous researches have concluded with the fact that much of the energy is wasted on transmission aspects rather than sensing in the scenario of sensor networks. This urges the need for developing a new model that captures the actual relationship between battery lifetime and classification accuracy. The hybrid model proposed combines Fisher Discriminant Analysis along with a Clustering based on Node with Maximum Energy. Also the work focuses to conclude by performing a trade- off between the crucial factors of lifetime and accuracy in the perspective of Wireless Networks.**

Keyword **– WSN, Analysis, Classification, Clustering, Lifetime Maximization.**

I. Introduction

Wireless sensor network is the combination of many more number of sensors which are combine together to form single wireless sensor network. sensor simply detects data and it communicates with the base. Lot of energy is wasted on communication aspects rather than on detection.This paper concentrates on efficient utilization of power rather than consumption of power. It reveals the relationship between the battery lifetime and classification accuracy. Major challenges in the sensor network is reduction of power consumption,by increasing the number iterations so that we can improve accuracy and hence by doing this lifetime of the power will decrease, maintaining the energy level during transferring information is difficult.To do so we are going to implement FDA along with NME.The energy consumption is maintained on the nodes so as to provide optimal routing which results in effective communication throughout the network without any loss of data. Not every node is active where some of the nodes may be in idle condition, so the detection of the data may varies as the time varies. We determine and separate erroneous data from the correct ones, and place them in respective classes.

So here we implement FDA ,this specific analysis focus on pattern classification and dimensionality reduction. Accuracy is characterized by the number of transmission that can be performed where they can be performed during training or by operations.

II. Related Works

Among the all the design goals of WSNs ,network lifetime is considered to the most important .Several solutions to maximize network lifetime are available ,and each approach provides different magnitudes of energy saving s and levels of efficiency. Most of the network lifetime optimization research works the clustering of sensors into group is a popular strategy to save energy and bandwidth, where we choose one node as the cluster header which having the high energy among them where, remaining of them will act as sub node. Maximizing the network lifetime in a energy efficient manner and fault tolerance has to be considered.

III. Network Lifetime Threats

Major challenge in the sensor network is reduction of power consumption. The nature of WSNs life limited because of the fact that most nodes operate on un chargeable power source like battery another reason is the ease of node damage, attempts to recharge the battery using solar or wind power has been proposed. Energy consumption in wireless systems is directionally proportional to the square of the distance, single hop communication is expensive in terms of energy consumption

IV. Proposing System

The principal component of proposing system is FDA along with NME. Dimensionality reduction pattern classification is done by FDA .

The proposing FDA is used for filtering events with negligible information Content analysis to validate the model for classification accuracy and the datas which are related are combined together to form under same classification known as pattern classification ;the repeated datas are reduced into single data. the header cluster is selected by the node consuming high energy which will communicate with the base station .The clustering approach performs with less number of nodes and other nodes are not participating in the process of sensing and transmitting the information which are received from the environment periodically .The non participating node consumes it energy as high as the initial stage and that will be considered as the network lifetime.

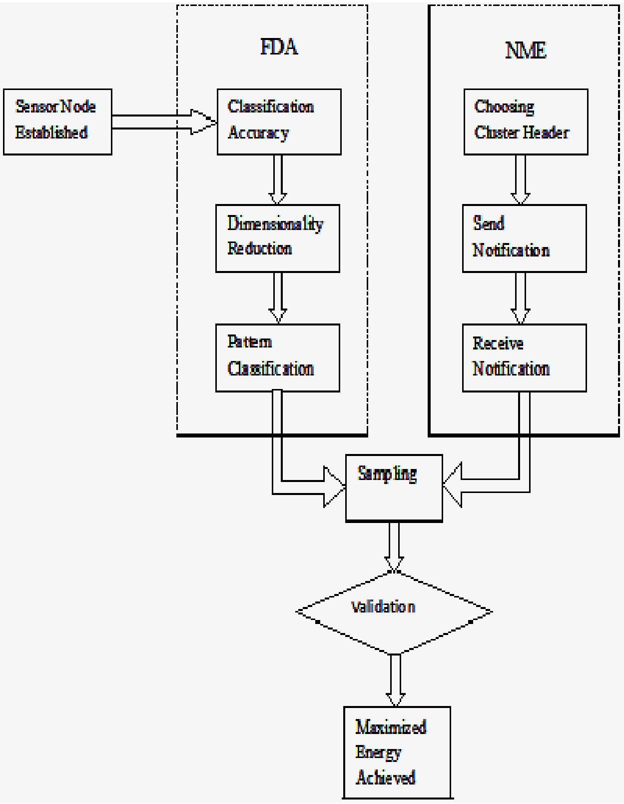

Fig. 1. Architectural Diagram

A. Dimensionality Reduction:

Three techniques used for data reduction namely aggregation ,filtering and sampling. Aggregation is the process in which the features from different layers are correlated to MAC layer features to form a reduced feature set.

Is the process of reducing the no of random variables under considerations and can be divided into future selection and future extraction ,it collects information within classes and between classes. In the machine learning and statistics, dimensionality reduction or dimension reduction is the process of reducing the number of random variables under consideration and can be divided into feature selection and feature extraction.

1) Feature Selection:

Future selection approaches try to find a subset of the original variables(also called features or attributes).Two strategies are filter (e.g. information gain)and wrapper(e.g. search guided by the accuracy) approaches. Also the combinational optimization problems. In some cases, data analysis such as regression or classification can be done in the reduced space more accurately than in the orginal space.

2) Feature Extraction:

Feature extraction transform the data in the high dimensional space to a space of fewer dimensions. The transformation may be linear ,as in principal component analysis (PCA).but many linear dimensionality reduction techniques also exit. For multidimensional data sensor representation can be used in dimensionality reduction through multi linear subspace learning.

3) Pattern Classification

The datas which are seprated from fault diagnosis are classified as the true data or the analysed data, the aggretated data, the repeated data are classified according to their categories for the future transmission. Once the data are classified according to their remedies then it plays a vital role in the efficient utilization of battery and it also reduces the unwanted usage of power in sensors.

B. NME:

The core idea behind NME clustering algorithm is choosing the node which having maximum energy .

1. Sending Advertisement And Scheduling:

NME selects cluster heads according to their energy; and sends the setup message to all other nodes in the sensor networks. Each group of cluster head broadcast the setup message inviting the other members to join in their group.

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2. Receiving Request And Information:

After receiving the setup message ;the regular sensor node sends the join message to the corresponding cluster header and also it sends the information about the energy remaining as well.

V. FISHER DISCRIMINANT ANALYSIS

PCA contains certain optimality properties in term of fault detection.PCA is not as well-suited for fault diagnosis because it does not take into account the information between the fault classes when determining the lower-dimensional representation. Fisher discriminant analysis (FDA), a dimensionality reduction technique takes into account the information between the classes and has advantages over PCA for fault diagnosis. For fault diagnosis, data collected from the plant during specific faults are categorized into classes, where each class contains data representing a particular fault. FDA is a linear dimensionality reduction technique, optimal in terms of maximizing the separation amongst these classes. It determines a set of vectors, ordered in terms of maximizing the scatter between classes while minimizing the scatter within each class. Define *n* as the number of observations, *m* as the number of measurement variables, *p* as the number of classes, and n_j as the number of observations in the j^{th} class. Represent the vector of measurement variables for the i^{th} observation as x_i. If the training data for all classes have already been stacked into the matrix X € R^{x*m}, then the transpose of the i^{th} row of X is the column vector x_i to understand Fisher discriminant analysis, first we need to define various matrices that quantify

the total scatter,
the scatter within classes,
and the scatter between classes.
The total scatter matrix is :

$$S_t \triangleq \sum_{i=1}^{n} (\mathrm{x_i} - \overline{\mathrm{x_i}})\ (\mathrm{x_i} - \overline{\mathrm{x_i}})^T \quad (1)$$

Where $\overline{x}$ is the total mean vector :

$$\overline{x} = \frac{1}{n} \sum_{i=1}^{1} x_i \quad (2)$$

With X_j , defines the set of vectors xi which belong to the class j , The within-scatter matrix for class j is:

$$S_t \triangleq \sum_{x_i \in X_j}^{n} (\mathrm{x_i} - \overline{\mathrm{x_j}})\ (\mathrm{x_i} - \overline{\mathrm{x_j}})^T \quad (3)$$

Where $\overline{x_j}$ is the total mean vector :

$$\overline{x_j} = \frac{1}{n_j} \sum_{x_i \in X_j}^{1} x_i \quad (4)$$

And the between-class-scatter matrix is :

$$S_b \triangleq \sum_{j=1}^{p} n_j (\overline{\mathrm{x_j}} - \overline{\mathrm{x}})(\overline{\mathrm{x_j}} - \overline{\mathrm{x}})^T \quad (5)$$

The total-scatter matrix is equal to the sum of the between-scatter matrix and the within-scatter matrix:

$$S_t = S_b + S_w \quad (6)$$

The objective of the first FDA vector is to maximize the scatter between classes while minimizing the scatter within classes: The second FDA vector is computed so as to maximize the scatter between classes while minimizing the scatter within classes among all axes perpendicular to the first FDA vector, and so on for the remaining FDA vector. It can be shown that the linear transformation vectors for FDA can be calculated by computing the stationary points of the optimization problem.

$$\max_{v \neq 0} \frac{V^T S_b V}{V^T S_w V} \quad (7)$$

Assuming invertible S_w where v € R_m. The FDA vectors are equal to the given vector wk of given value problem:$S_b \mathbf{w}_k = \lambda_k S_w \mathbf{w}_k$Where the given values λ_k indicate the degree of overall separatability among the classes by projecting the data onto w_k. The FDA vector can be computed from the generalized given value problem as long as S_w is invertible. This will almost always be true provided that the number of observations n is significantly larger than the number of measurements m (the case in practice). Because the direction and not the magnitude of wk is important, the Euclidean norm (square root of the sum of squares of each element) of wk can be chosen to be equal to 1 (||w||=1).

The first FDA vector is the given vector associated with the largest given value associated with the second largest given value and so on. A large given value λ_k indicates that when the data in the classes are projected onto the associated given vector wk there is overall a large separation of the class means relative to the class variances. And consequently a large degree of separation among the classes along the direction w_k. Since the rank of S_b is less than p, there will be at most p-1 given values which are not equal to zero and FDA provides useful ordering of the given vectors only in these directions. It is useful to write the goal of FDA more explicitly in terms of a linear transformation. Define the matrix W_p € R_m*(p-1) with the p-1 FDA vectors as columns. Then the linear transformation of the data from m-dimensional space to (p – 1)- dimensional space is described by: $Z_i = W_p{}^T x_i$ Where z_i € R(p-1).FDA computes the matrix W_p such that data $x_1,\ldots,x_n$ for the p classes are optimally separated when projected into the (p - 1) dimensional space. In the case where p is equal to 2, this is equivalent to projecting the data onto a line in the direction of the vector w, for which the projected data are the best separated.

A. Fault Detection and Diagnosis

When FDA is applied for pattern classification, the dimensionality reduction technique is applied to the data in *all* the classes simultaneously. More precisely, denote W_a € R^{m*a} as the matrix containing the given vectors w_1, w_2, w_a computed

The discriminant function can be derived

$$g_i(x) = -\frac{1}{2}\left(X - \bar{X}_j\right)^T W_a\left(\frac{1}{n_j - 1}W_a{}^T S_j W_a\right)^{-1} W_a{}^T \frac{1}{2}\left(X - \bar{X}_j\right)^T + \ln\left(p_i\right) - \frac{1}{2}\ln[\det(\frac{1}{n_j - 1}W_a{}^T S_j W_a)] \tag{8}$$

Where,

S_j , $\bar{x}_j$ and nj are defined .In contrast to PCAl , FDA uses the class information to compute the reduced dimensional space. In contrast to PCAm, FDA utilizes all p fault class information when evaluating the discriminant function for each class. FDA can also be applied to detect faults by defining an additional class of data, that collected during normal operation conditions, to the fault classes. The proficiency of fault detection depends on the similarity between the data from the normal operating conditions and the data from the fault classes in the training set.

When there exists a transformation W such that the data from the normal operation conditions can be reasonably separated from the other fault classes. Using FDA for fault detection will produce small missed detection rates for the fault classes. unknown faults associated with data outside of the lower-dimensional space defined by the FDA vectors. a residual-based FDA statistic which together can detect both faults associated with data inside the space defined by the FDA vectors and faults associated with data outside of this space. The advantages of using the FDA statistics instead of the PCA statistics is that the fault classification information can be taken into account to improve the ability to detect faults. The disadvantage is that the FDA statistics required that fault classification information to define its lower-dimensional space (define by W). only the first p-1 given vectors in FDA maximize the scatter between the classes while minimizing the scatter within each class. The rest of the m-p+1 given vectors corresponding to the zero given values are not ordered by the FDA objective .The ranking of these given vectors is determined by the particular software package implementing the given values decomposition algorithm, which does not order the given vectors in a manner necessarily useful classifications. However, more than p-1 dimensions in a lower dimensional space may be useful for classification, and a produce to select vectors beyond the first p-1 FDA vectors can be useful. Here two methods are described which use PCA to compute additional vectors for classification. One method is to use FDA for the space defined by the first p-1 given vectors, and to use the PCAI vectors for the rest of the m-p+1 vectors, ordered from the PCA vectors associated with the high variability to the vectors associated with the lower variability. If the reduction order $a \le p - 1$,

If $a \ge p$, the alternative discriminant function is used:

$$g_i(x) = -\frac{1}{2}\left(X - \bar{X}_j\right)^T W_{mix,a}\left(\frac{1}{n_j - 1}W_{mix,a}{}^T S_j W_a\right)^{-1} W_{mix,a}{}^T \frac{1}{2}\left(X - \bar{X}_j\right)^T + \ln\left(p_i\right) - \frac{1}{2}\ln[\det(\frac{1}{n_j - 1}W_{mix,a}{}^T S_j W_{mix,a})] \tag{9}$$

Where, $W_{mix,a}$ = [Wp-1 Pa-p+1] and Pa-p+1 is the first a – p+1 columns of the PCAI loading matrix P .When this method is used for diagnosing faults, it will be referred to as the FDA-PCAI method

B. Reduction Order

No reduction of dimensionality would be needed if the covariance matrix and mean vector were known exactly.

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Errors in the sample covariance matrix occur in practice. Data dimensionality reduction provided by FDA may be necessary to reduce the misclassification rate. A popular method for selecting the reduction order for dimensionality reduction methods is to use cross-validation. This approach separates the data into multiple sets: the training set and the testing (or validation) set. The dimensionality reduction procedure is applied to the data in the training set and its performance is evaluated by applying the reduced dimension model to the data in the testing set for each reduction order. The reduction order is selected to optimize the performance based on the testing set.

For example, if the goal is fault diagnosis, the order of the reduced model would be specified by minimizing the misclassification rate of the testing set. Cross-validation is not always practical in fault diagnosis applications because there may not be enough data to separate into two sets. In this situation, it is desirable to determine the order of the dimensionality reduction using all the data in the training set. The error of a model can be minimized by choosing the number of independent parameters so that it optimally trade-off the bias and variance contributions on the mean squared error. In a effort to minimize the mean squared error, criteria the form:(prediction error term) + (model complexity term) have been minimized to determine the appropriate model order. And the model complexity term is a function of the number of independent parameters and the amount of data in the training set. The order can be determined by computing the dimensionality a that minimizes the information criterion:

$$f_m(a) + \frac{a}{ñ} \qquad (10)$$

Where fm(a) is the misclassification rate (the proportion of misclassification rate which is between 0 and 1) for the training set by projecting the data onto the first a FDA vectors, and ñ is the average number of observations per class. The misclassification rate of the training set, fm (a) indicates the amount of information contained in the first a FDA vectors. The misclassification rate of the training set typically decreases as a increases. For new data (data independent of the training set), the misclassification rate initially decreases and then increases above a certain order due to over-fitting the data.

The model complexity term $a/\tilde{n}$ is added to penalize the increase of dimensionality. The scaling of the reduction order a by the average number of observations per class, ñ has some intuitive implication. To illustrate this, consider the case where the number of observations in each class is the same n_j = ñ. It can be shown using some simple algebra that the inclusion of the $a/\tilde{n}$ term in ensure that the order selection produce a value for a less than or equal to ñ. In words, this constraint prevents the lower dimensional model from having a higher dimensionality than justified by the number of observation in each class. The model complexity term $a/\tilde{n}$ can also be interpreted in terms of the total number of misclassifications per class. Defining m(a)as the total number of misclassifications in the training set for order a and assuming that n_j = ñ, the information criterion can be written as: $(m(a)/p\tilde{n}) + a/\tilde{n}$ Where n = pñ is the total number of observations. Let us consider the case where it is to be determined whether a reduction order of a + 1 should be preferred over a reduction order of a. Using the information criterion and recalling that a smaller value for the information criterion is preferred, a reduction order of a + 1 is preferred if :

$$m(a+1)/p\tilde{n} + (a+1)/p\tilde{n} < m(a)/p\tilde{n} + a/\tilde{n}$$
(11)

This equivalent to:

$$\text{m(a)/pn}\, m(a)/p\tilde{n} - m(a+1)/p\tilde{n} > 1 \qquad (12)$$

The complexity term does not allow the reduction order to be increased merely by decreasing the number of misclassifications, but only if the decrease in the total number of misclassifications per class is greater than 1.The above analyses indicate that the scaling of a in the model complexity term $\frac{a}{ñ}$ in the information criterion is reasonable.

VI. FDA Methodology

FDA can be implemented as the main aspects of finding the incomplete data and diagnosis from the fault data. In our proposed model we implement the following metrics namely Predictability, Schedulability, Network lifetime and energy.

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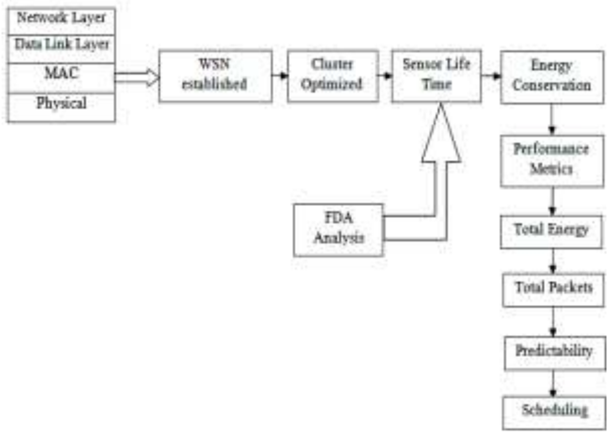

Fig. 2. FDA methodology Diagram

A. Scheduling:

In the Schedulability Analysis stage, Schedulability test results provide the necessary information to all running scenarios. If the running case is not schedulable, the feedback process can be used to alternate the WSN deployment plan or other configuration parameters (such as coverage range), which can be used to redesign the system. The problem, however is that no such formal network lifetime analysis methods currently exist. Thus, we approach this problem by first formally introducing the problem of hard network lifetime constraint. Then, we present a simple closed form test for determining whether a sensor set is schedulable or not in terms of the N-of-N lifetime for the NME cluster head selection algorithm.

B. Predictability:

In the operational stage the appropriate classifier is used for prediction based on the activity state of the measurements. In this setup, we associate with each state a number training samples.

C. Performance metrics:

The performance measures of interest are the classification accuracy and operational lifetime, which is the lifetime spent in the operational stage, not in the training stage. The two main parameters available for configuring the sensor network are the CSMA back-off rates (the reciprocal of the mean backoff time), and the fraction of the lifetime spent in the training stage.

D. Energy conservation:

The energy consumption of sensor nodes, and thus the lifetime of the network, is dominated by energy expended on communication.

Battery capacity is characterized by the number of transmissions (and thus measurements) that can be performed, whether they are during training or operation. As every measurement corresponds to one transmission, the expected network lifetime is inversely proportional to the node throughput in our model. Sensor lifetime: By efficient utilization of energy, we can enhance the life time of the sensors.

E. Cluster optimization:

Clustering require partial knowledge on system energy levels and environment conditions. To maximize the network lifetime, some schemes pursue short-term fairness in time by sharing the energy consumption loading, while some others try to form clusters according to the geographical position of sensors.

F. FDA Analysis:

It is combination of both Dimension ability Reduction and Pattern classification. It determines canonical direction for which the data is most separated when projected on line in some direction.

VII. Simulation Analysis

A. Energy

The energy of the node increases by implementing FDA Energy is most important design factor for sensor networks. Saving power during the operation of the electronic device could be achieved on more than one level.

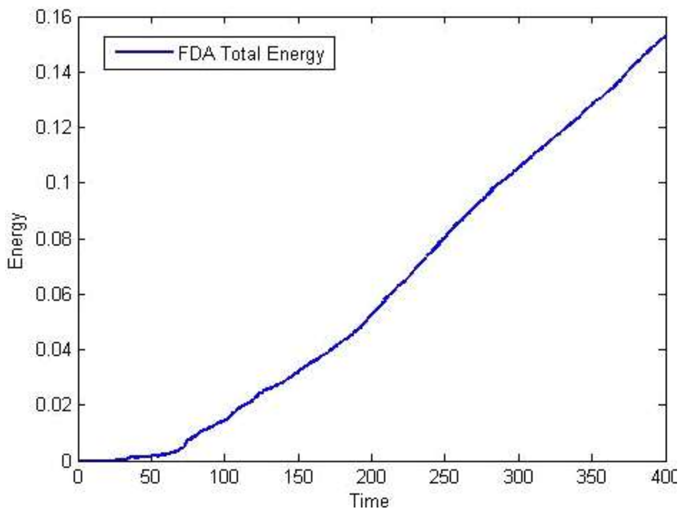

Fig. 3. Simulation analysis for FDA in Total energy

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B. Total Packets

The simulation analysis concludes as fault data increases then lifetime of the battery will decrease. The proposed scheme can be efficiently computed by sending many number of packets at the same time the it make respective changes in lifetime of the battery also. In the graph representation it started deviated from the time interval between 100-150 packets and then gradually increases between every successive transmission. Once the detection of fault packets identified then it slows the rate of transmission between packets 150-200 packets. The maximization of energy can be achieved by ignoring the unnecessary transmission of fault packets. It can be easily indentified in the plotted graph. Finally the resultant packets reaches the destination without any delay or disturbance.

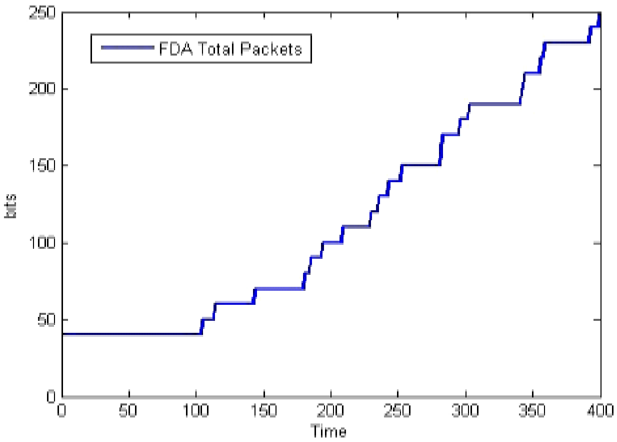

Fig. 4. Simulation analysis for FDA in Total packets

C. Predictability

We should have a confidence to determine to determine in advance whether the specific critical tasks can be performed completely under current energy budgets, as well as within the time constraints. To provide to time critical WSN applications, and it is important to understand how the system behave .

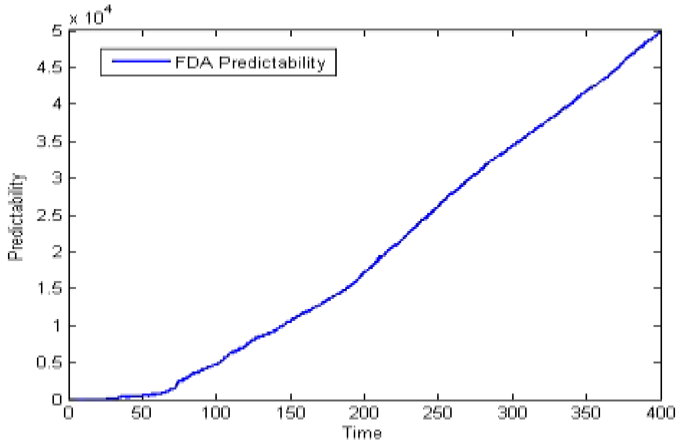

Fig. 5. Simulation analysis for FDA in Predictability

D. Schudelability:

Schudelability test result provide the necessary information to all running scenarios .If the running case is not schedulable, the feed back process can be used to alternate the WSN deployment plan or other configuration parameters(such as coverage area),which can be used to re-design the system.

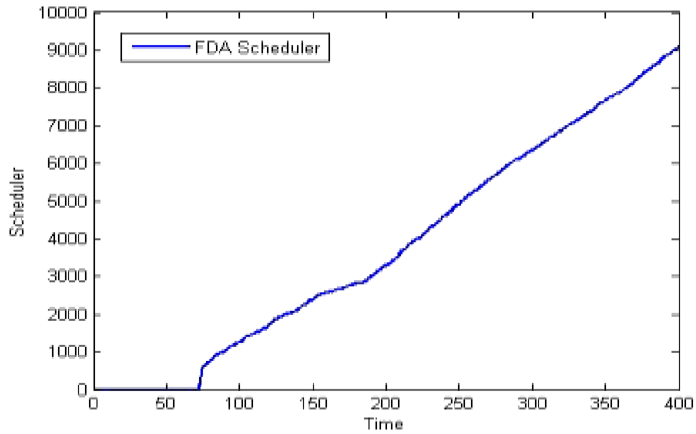

Fig. 6. Simulation analysis for FDA in Scheduler

E. Network Lifetime:

The Density Property of the WSNs it is possible the network life time and also efficiently balance the energy consumption load across the network .Energy/power consumption of the sensing device should be minimized and Sensor nodes should be energy efficient since their limited energy resources Determine the life time. To conserve power the nodes should shut off the Radio power supply when not in use.

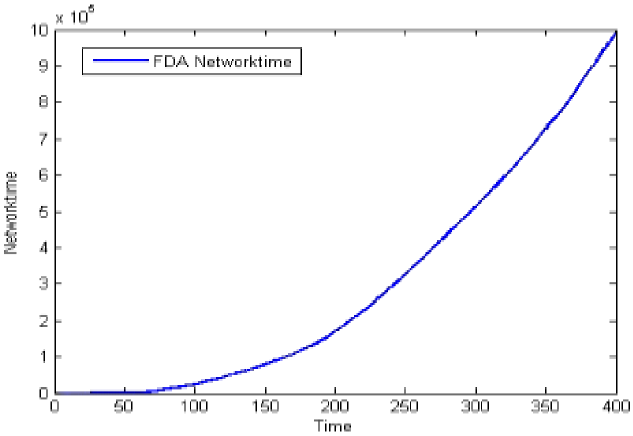

Fig. 7. Simulation analysis for FDA in network lifetime

VIII. RESULTS AND DISCUSSION

A. Energy:

FDA have the same residual energy in the beginning ,but FDA gradually has more minimum residual energy than normal network after a certain period of time ,the result shows that FDA further prolongs the network lifetime when compared with normal network.

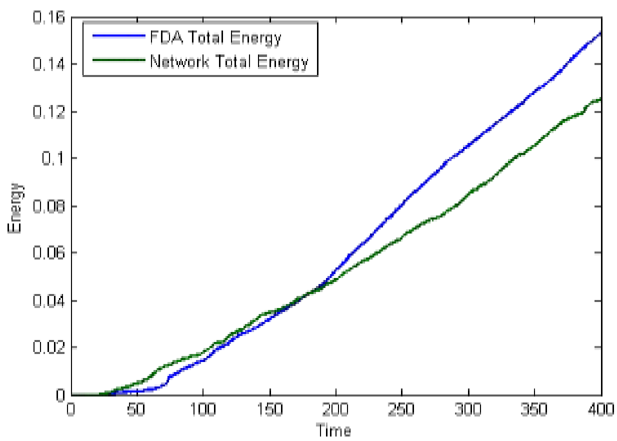

Fig. 8. Comparing the total energy in normal WSN and FDA WSN

B. Total Packets:

The transmission of number of packets increases with the initial energy increases. Their performances are also compared under the same mean values of energy ,but with different variances. When the initial energy level is low there is no significant performances differences between normal network and FDA network. But due to reduction of number of replicated data; the transmission power increases my sending many more number of packets within limited period of time this reaction cause it impact the energy level of sensor.

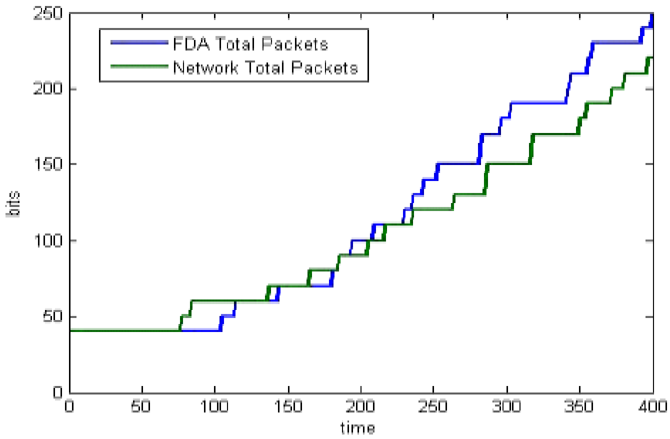

Fig. 9. Comparing the Total number of packets between the normal WSN and FDAWSN

C. Predictability And Schedulability:

Predictability and schedulability which complements each other ,By FDA it reduces number of transmission and hence increases the number of measurements .FDA helps to decide whether the faults data's are eliminated or not. The replication of messages was unnecessary by the reduction order. The amount of energy consumed by a sensor node depends on the role it serves ,as well as the workload it handles. Data's are sensed and transmitted in each round periodically. From the (Figure 10) the most number of deviations starts at the initial level of energy and then it maintain a regular interval of time for sending packets to its destination it also ensures whether each and every node in the network have sufficient energy to reach its destination. From the (Figure 11),it is obvious from the simulation result that by exploiting the density property of the WSNs it is possible to enhance the network lifetime and also efficiently balance the energy consumption load across the network. It shows at the initial level both networks maintain the same level of energy and hence it starts deviates from mid of the network finally the network with FDA achieve better performances.

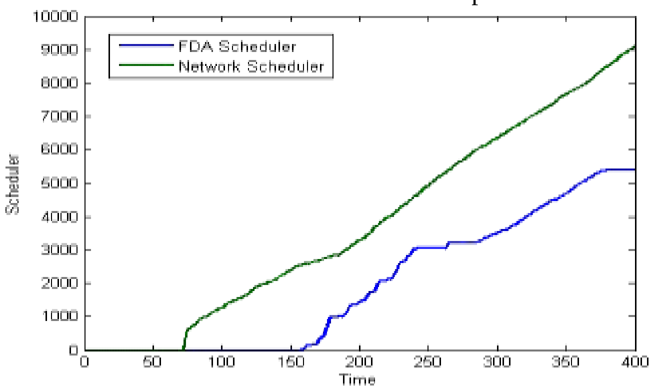

Fig. 10. Comparing the Scheduler between the normal WSN and FDAWSN

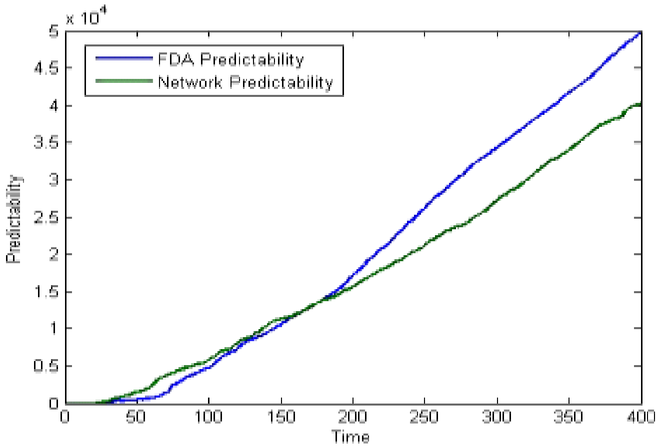

Fig. 11. Comparing the Predictability between the normal WSN and FDAWSN

D. Network Lifetime:

Network lifetime is perhaps the most important for the evaluation of sensor network. The network can only fulfill its purpose as long as it is consider "alive", but not after that .The lifetime of the sensor node depends basically on two factors: how much energy it consumes over time and how much energy is available for its use. Our proposed model FDA provides maximum amount of energy the following Figure determines how the FDA network life time deviates from the normal network. Maximum number of packets have been sent when energy level is peak as well as the coverage area.

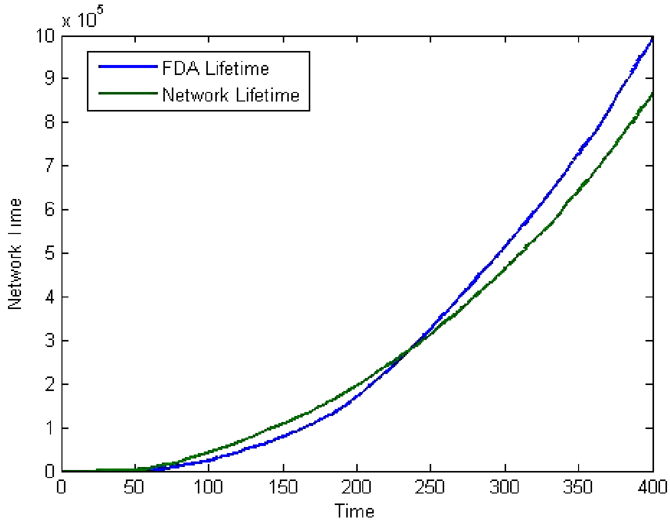

Fig. 12. Comparing the network life time between normal WSN and FDA WSN

IX. Conclusion

In this work, an intelligent, adaptive, and fast system for detecting and sending of datas to its destination. In the proposed technique FDA it ensures that the efficient utilization of battery will play vital role in the maximization of life time of the network. In this paper we have addressed the parameters such as Schedulability, Predictability, Energy and Network lifetime. It provides a trustworthy system behavior with a guaranteed hard network lifetime is a challenging task to safety- critical and highly- reliable WSN application. Our experiment result shows that the FDA achieves significant performancece improvement over normal network.

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